

Privatizing Government-Sponsored Health Insurance: Medicare Advantage vs. Traditional Medicare*

Zarek Brot^{a,b,c}, Yalun Su^{a,b}, Boris Vabson^b,
Scott Bilder^d, Barton Jones^d, Iman Mohammadi^d,
Zulkarnain Pulungan^d, and Christie Teigland^d

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Abstract

We study the consequences of enrollment in private Medicare Advantage (MA) plans. We longitudinally link claims data from public Medicare (FFS), MA, and commercial insurance. We compare those who initially enroll in MA to those who enroll in FFS, just before and after they qualify for Medicare at age 65. MA reduces health care use by 6% in the first year of enrollment relative to FFS, but raises federal insurance costs by 15% (4% net of additional benefit generosity). Managed care policies matter: HMO plans generate sizable utilization reductions and fiscal savings, while PPO plans generate sizable fiscal costs.

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^a University of Chicago.

^b Healthcare Markets and Regulation Lab, Harvard University.

^c NBER.

^d Inovalon.

Economists have long debated whether government-sponsored services are more efficiently provided directly by the public sector, or outsourced to private firms. Competition between private firms may grant them better incentives to improve operations than the public sector, but, when outsourcing contracts are imperfectly designed, these gains might accrue to the firms rather than to beneficiaries or the government ([Hart et al. 1997](#)). In the United States, the Medicare and Medicaid programs, which were initiated as government-operated programs, have rapidly shifted towards private provision over the 21st century. Half of Medicare beneficiaries and three-quarters of Medicaid beneficiaries now have their medical coverage administered by a private insurer.

What are the consequences of the privatization of government-sponsored health insurance? We focus on the Medicare Advantage (MA) program, one of the largest privatization schemes in the United States. The MA program allows Medicare beneficiaries to opt out of the publicly-administered fee-for-service (FFS) Traditional Medicare plan and instead enroll in a privately-administered plan. In 2024, the federal government paid over \$494 billion in reimbursements to MA insurers, 7.7% of the annual federal budget ([MedPAC 2025](#)). The goal of the MA program has been to allow private insurers to use their expertise to contain costs, which they do by using managed care tools that impose non-price restrictions on beneficiary utilization, such as limited provider networks, prior authorization, and referral requirements. To entice beneficiaries to accept these restrictions, MA plans offer more generous financial coverage and supplemental benefits.

In this paper, we evaluate the consequences of enrollment in the MA program. We take a broad view, estimating its effects on beneficiary utilization and health as well as the fiscal outlook of Medicare facing the federal government. Any attempt to do so faces a major challenge: since MA and FFS offer different benefits, they attract different sorts of enrollees. Due to these differences, academics and policymakers believe that MA is favorably selected, meaning that beneficiaries who are healthier and/or have low propensity to seek treatment are more likely to enroll in MA plans ([Newhouse et al. 2013, 2015](#), [Brown et al. 2014](#)).

This selection matters for two reasons. First, estimating unbiased causal effects of MA enrollment on outcomes requires researchers to control for differential selection. Due to data limitations, researchers have traditionally been limited to research designs that require no differential selection into MA based on factors not observed within traditional claims data, which is unlikely to be true. Even the best of prior studies have encountered serious worries about selection bias ([Nicholas et al. 2024](#)). Second, MA plans are paid on a risk-adjusted basis, receiving greater payments if they enroll higher-risk enrollees. Some have worried that favorable selection inflates reimbursements paid to MA plans above their true cost of insuring enrollees ([Ryan et al. 2023](#), [MedPAC 2024](#)).

We introduce a first-of-its-kind dataset that allows us to separate the roles of selection and treatment in driving MA vs. FFS differences. We bring together private health insurance data from Inovalon, which tracks health care use and enrollment for a sizable set of the privately-insured population (including both MA and other sources of private coverage). We link individuals longitudinally between Inovalon's data and FFS Medicare data, resulting in a combined dataset covering the 2012 to 2019 period. We are thus uniquely able to follow individuals' use of health care as they transition across different sources of insurance coverage. This dataset provides us with one additional set of observables previously unavailable to researchers: health care utilization *just before* individuals qualify for Medicare.

We focus on beneficiaries who have employer-sponsored insurance coverage at 64 and transition into

Medicare at the age of 65, enrolling in either MA or FFS. Simply comparing MA enrollees to FFS enrollees *after* Medicare enrollment, even when controlling for various observable factors, risks confounding the impact of MA enrollment with selection bias coming from underlying differences between the two groups. We reduce this selection bias by also comparing the two groups at age 64,. Differences at this time period reflect *only* selection, since both groups are still enrolled in employer-sponsored plans. Any permanent differences between MA and FFS enrollees that affect outcomes at age 65 are likely to have similar effects at age 64, and so our approach is likely to reduce selection bias substantially. Implementing it reduces to a standard difference-in-differences approach.

We estimate that MA reduces health care utilization in the first year of enrollment by 6.2% relative to FFS, with larger effects in further years of enrollment. Our approach to selection matters tremendously: if we were to *only* use post-enrollment comparisons between MA and FFS enrollees, we would conclude that the effects of MA were more than three times as large (reductions of 19.2%), despite controlling for a rich set of health, demographic, and socioeconomic factors. This arises from the fact that there are substantial baseline differences in utilization between future MA and future FFS enrollees even net of these factors.

Differences between MA and FFS post-enrollment arise from the fact that utilization increases sharply after a transition from employer-sponsored insurance to FFS, whereas MA plans hold utilization roughly at the same level as employer-sponsored plans. MA primarily reduces the use of inpatient and post-acute care, while slightly increasing spending on outpatient care and prescription drugs. The largest reductions come from relatively sicker beneficiaries in lower-income neighborhoods, whereas healthier and high-income-neighborhood beneficiaries experience slight *increases* in utilization. We find mixed results on quality of care: MA improves quality of care on some margins (less preventable hospitalizations; greater use of high-value drugs) but reduces quality on other margins (use of breast cancer screening for women and blood sugar screening for diabetics).

MA's distinguishing feature from FFS is that MA plans employ managed care policies. We explore whether the effects of MA vary across plans by the extent to which they use such policies. We compare HMO plans, which impose stronger restrictions on beneficiaries, to PPO plans, which impose weaker restrictions. We find that HMO plans reduce the use of care substantially relative to FFS, whereas MA PPO plans cause utilization to *rise* relative to FFS enrollment. This latter effect likely comes from the fact that PPOs reduce cost-sharing without compensating by applying sufficiently strong non-price utilization restrictions. Differences between HMOs and PPOs explain much of our other sources of effect heterogeneity. For instance, while the average MA enrollee reduces inpatient spending and increases outpatient spending, this arises due to the fact that HMOs reduce inpatient use, while PPOs increase outpatient use, *not* due to substitution between the two sources of care. Similarly, a part of the heterogeneous effects of MA enrollment across beneficiaries is driven by differential propensities to enroll in HMO plans. In contrast to these results, differences in other economic factors, such as MA plan competition, account for only minor differences.

While these utilization reductions allow MA plans to deliver health care at lower cost than the public FFS program, these gains may not necessarily get passed through to the government. We use our estimates to assess the fiscal consequences of MA. We measure the difference in costs to CMS of enrolling beneficiaries in MA relative to forcing them into FFS instead. Despite the fact that MA plans are able to reduce beneficiaries' health expenses, the MA program nonetheless appears to raise the fiscal cost of Medicare by

\$687 per beneficiary-year (a 15.0% increase relative to FFS enrollment).

We explain the fiscal effects of MA through two mechanisms. First, MA plans offer more generous cost-sharing than FFS, and cover additional supplemental services, both of which require additional financing. We estimate that this accounts for \$521 per beneficiary-year. When considering *only* the cost of providing standard FFS coverage, we estimate that MA instead only raises fiscal costs by 3.6%. Second, imperfections in the risk adjustment formula drive plan payments up. Plans are paid more to cover beneficiaries who are expected to incur greater expenses. However, the risk scores are coarsely based on spending by FFS enrollees with similar diagnoses. MA enrollees are favorably selected in that they use less care than FFS enrollees with identical diagnoses. Comparing future MA and FFS enrollees at 64 with like risk scores (who would generate identical reimbursements for MA plans), we find that MA enrollees are 11.1% less costly to insure than their risk scores would imply. Plan generosity and favorable selection each explain roughly half of the gap between MA's effect on utilization and its effect on government expense. Absent both, the MA program would potentially save the government a substantial sum of money.

These fiscal consequences differ substantially between HMO and PPO plans. In many specifications, particularly those where we consider the costs of providing only standard FFS coverage, HMOs *save* money for the federal government due to their large reductions in beneficiary spending, while PPOs raise the cost of Medicare substantially. This is surprising given that HMOs are quite favorably selected relative to FFS, whereas PPOs are not favorably selected at all.

We conclude that privatization of health insurance *can* reduce the cost of its provision for the government without clear losses for beneficiaries, though it does not reduce costs in practice. The potential for cost reductions, however, *only* arise through the aggressive use of managed care tools, which government-run plans generally can or will not use. In contrast, when private plans are more weakly differentiated from the public offering (as PPO plans are), there are little gains to be realized from privatization, but the costs of imperfect contracting remain.

Moreover, although we find that favorable selection increases MA reimbursement rates in general, *across plans*, favorable selection is not necessarily an indicator of fiscal consequences. While selection is primarily driven by HMOs, they also have less deleterious fiscal consequences than PPOs. This arises from the fact that MA plans must fund the supplemental benefits that attract favorably-selected beneficiaries through rebates, which they only receive if they reduce utilization. This creates a perverse positive correlation between a plan's ability to achieve the goals of the MA program and the extent to which it earns excess payments from imperfect risk adjustment.

We contribute to a long literature on the economics of the MA program. Prior researchers have struggled to find a way to account for the role of unobservable factors in driving selection into MA ([Nicholas et al. 2024](#)). Around 90% of studies in this literature rely on assuming away any differential selection into MA vs. FFS on factors not observable within standard CMS data to interpret their findings as causal ([Agarwal et al. 2021](#), [Ochieng and Fuglesten Biniek 2022](#)), though some studies use these observables in a more sophisticated way ([Curto et al. 2019](#), [Jung et al. forthcoming](#)). We show that substantial risk-adjusted differences between MA and FFS enrollees exist even *before* they enter Medicare, suggesting that the risk adjustment strategies used in this prior studies may not fully correct for selection bias. Our approach is closer in spirit (and our estimates closer in magnitude) to other recent difference-in-differences approaches ([Duggan et al.](#)

2018, Schwartz et al. 2021, 2023). However, these studies have often been limited to small sample sizes and/or have only measured a narrow set of outcomes, both problems that are solved by our new dataset.

We also join a literature on the fiscal consequences of MA. Researchers have emphasized the role of favorable selection under imperfect risk adjustment in driving up the cost of Medicare (Newhouse et al. 2013, 2015, Brown et al. 2014). They have done this by focusing on beneficiaries who switch from FFS to MA, which is quite uncommon, leaving the potential that selection in this group may not reflect selection of inframarginal MA enrollees. We confirm the presence of favorable selection among *initial* enrollees. Our estimates of selection are slightly lower than many recent comparable switcher estimates (Jacobson et al. 2019, Lieberman et al. 2023b), though not all (MedPAC 2024). We find, echoing other recent work, that MA has resulted in increased fiscal costs of the Medicare program (MedPAC 2025). We estimate smaller fiscal effects of MA than prior studies (significantly smaller when accounting for differential plan generosity), though the differences in our estimates reflect both our ability to further correct for selection using pre-Medicare utilization *and* the fact that we are only able to employ this correction for 65-year-olds, rather than for all MA enrollees.

Our results also highlight the importance of managed care in health insurance. Prior studies have shown that specific managed care strategies have large impacts on curbing waste and reducing the cost of providing insurance, including prior authorization (Eliason et al. 2021, Brot et al. 2023, Gandhi and Shi 2025), retrospective claims auditing (League 2023, Shi 2024), and restrictive provider networks (Gruber and McKnight 2016, Wallace 2023). We show that the widespread use of managed care policies under private MA plans, in contrast to public FFS, explains virtually all of the ability of Medicare privatization to contain costs. Our results are akin to a small literature that has linked “macro” phenomena in health insurance to changes in managed care, including studies that show that the extent of use of managed care also explains cost containment under Medicaid privatization (Dranove et al. 2021, Agafiev Macambira et al. 2023) and the slowdown in private health care spending in the 1990s (Pinkovskiy 2020).

Finally, we contribute to a broader literature on the merits and demerits of privatization, in insurance markets and beyond. Our results highlight the trade-off in privatization introduced by Hart et al. (1997): While (some) MA plans are better able to control utilization relative to FFS, MA raises fiscal costs due to the government’s inability to fully condition plan payments on enrollees’ expected costs. MA’s comparative advantage in curbing spending comes from its use of managed care, which the FFS program is statutorily prohibited from using. A major benefit of privatization in this context is therefore private plans’ ability to implement policies without requiring passing legislation or other political constraints (Boycko et al. 1996).¹ We also demonstrate the role of heterogeneity in potential contractors as a key determinant of the effect of privatization.²

¹Similarly, Layton et al. (2022) find that a benefit of Medicaid privatization in Texas was the ability of private plans to avoid excessively onerous statutory restrictions on drug coverage that existed in the public system.

²Other studies have, similarly, found substantial heterogeneity across MA plans’ contribution to enrollee mortality (Abaluck et al. 2021) and private Medicaid plans’ effects on utilization (Geruso et al. 2023).

1 Institutional Background

The Medicare Advantage program serves as a privately-administered alternative to the traditional publicly-administered Medicare Parts A & B, which provide insurance for hospital and medical professional services. The goal in establishing private options for Medicare coverage was twofold: First, to broaden the choices available to beneficiaries; and second, to leverage managed care to improve the efficiency of the program (McGuire et al. 2011). While CMS had experimented with private managed care plans starting in the early years of the Medicare program, this was expanded greatly following the Tax Equity and Fiscal Responsibility Act of 1982, which effectively established the predecessor to the modern MA program, then known as Medicare Part C, including the prevailing system of capitated payments (Berenson and Dowd 2008). The modern system, including the renaming to Medicare Advantage, occurred as a result of the 2003 Medicare Modernization Act. The MA program has become increasingly popular since this point. While in 2003, only 13% of Medicare beneficiaries were enrolled in an MA plan, in 2023, the share was slightly over half (Ochieng et al. 2023b).

Under the MA program, the plan sponsor, a health insurer, is completely responsible for administering and financing health insurance coverage for the beneficiaries that they enroll. In exchange for performing this service, the insurer is paid on a capitated, per-enrollee basis. The payment is roughly intended to cover the expected cost of providing insurance. The insurer is the sole residual claimant on any savings net of this payment, providing them with strong incentives to engage in activities that reduce the cost of coverage. The federal government may also fiscally benefit from this arrangement, to the extent that MA plans' lower cost of coverage are reflected in MA plans' bids, which in turn determine government reimbursements.

1.1 Enrollment

Medicare beneficiaries may choose between enrollment in the public Traditional Medicare program or the private MA program. Under the Traditional Medicare program (which we refer to in shorthand as FFS due to its fee-for-service reimbursement structure), beneficiaries receive medical coverage via Medicare Parts A and B, which are administered by the Centers for Medicare and Medicaid Services (CMS). Medicare Parts A and B provide insurance against the cost of medical care (including care at hospitals and other facilities, as well as non-institutional directly from medical professionals). FFS enrollees face minimal restrictions on what care is covered, though CMS does engage in some auditing of claims for waste and fraud, along with other program integrity efforts (League 2023, Shi 2024). Under the FFS program, beneficiaries are responsible for some share of all health care costs, including in the form of deductibles and co-insurance. In 2021, about 40% of Medicare FFS enrollees chose to buy a supplemental Medigap insurance plan to cover this residual cost-sharing, with another 50% receiving supplemental coverage either from a former employer (through a retiree plan) or through Medicaid; the remaining 10% had no supplemental coverage (Ochieng et al. 2023a).³ For prescription drug coverage, beneficiaries in Medicare FFS must enroll in a Part D plan.

³We will not cover the Medigap market in depth. However, one institutional feature relevant in our setting is that Medigap is guaranteed issue and not subject to underwriting (i.e., plans are required to offer coverage and cannot vary premiums based on expected costs), but only, in most states, for those who initially enroll in a plan within 6 months of entering the Medicare program. Those who try to buy Medigap plans later in their Medicare enrollment spell face full risk rating in most states. This makes switching from an MA plan into the FFS program quite costly for sick beneficiaries, leading to low switching rates between the two

Medicare Part D is fully privatized, even for those enrolled in medical coverage through the public Medicare program, leaving enrollees to choose from one of many possible private drug plan options.

As an alternative to FFS, beneficiaries can instead enroll in the private MA program, and specifically choose from any of the MA plans offered in their county of residence.⁴ MA enrollees must pay the Part A and B premiums to CMS, and (in some cases, described below) a premium to the MA plan directly. CMS releases quality assessments of different MA plans, to help inform beneficiaries' choice of plan. MA enrollees are not permitted to buy supplemental Medigap plans. However, as we discuss below, cost-sharing in MA plans tends to be significantly lower than under stand-alone FFS, obviating the need for supplemental coverage. Additionally, most MA insurers offer versions of their plans with integrated drug coverage; the vast majority of MA enrollees (over 90%) enroll in such plans. Hence, one benefit of MA enrollment for beneficiaries is that it serves as a one-stop shop for coverage, rather than requiring them to shop across multiple insurance market segments.

1.2 Plan Payment

In exchange for providing insurance services, CMS renders payments to MA insurers. The primary payment is an amount meant to reimburse plans for standard medical coverage (i.e., what is covered by Parts A and B). CMS begins by setting and announcing a benchmark rate B for each county, each year. Benchmarks are meant to reflect the expected cost of insuring an average enrollee in that county, under standard Medicare FFS cost sharing levels, though plans with higher quality scores are awarded with higher benchmarks. Each plan seeking to offer coverage in that county submits a bid, b , meant to reflect their own expected costs of providing coverage. If the bid is greater than the benchmark, the plan must charge a basic premium to enrollees equal to $b - B$, which would cover Part A and B services. If the bid is less than the benchmark, plans will not charge a basic premium. Plans can also charge supplemental premiums, either to cover additional services outside of basic Part A and B coverage, or to cover Part D coverage. Bids below the benchmark are typical; on average, MA plans in our sample bid at 88% of the benchmark.

Plans face positive incentives to bid lower since this lowers the premiums they must charge enrollees. However, they cannot charge negative premium amounts as a result of bidding further below the benchmark. They therefore face an additional incentive to lower their bids: Plans receive a ‘rebate’ payment that is increasing as plans bid farther below the benchmark. Unlike the base payment, which corresponds to the bid and which is meant to cover core Medicare services, the rebate must, actuarially, be allocated entirely to supplemental benefits (including such benefits as hearing and vision coverage, gym membership benefits, or premium/cost-sharing reductions). The rebate is set to be equal to $\alpha(B - b)$, where α is between 0.5 and 0.7 and depends on the plan’s quality rating. The residual difference between benchmark and bid is returned back to the federal government. Hence, this is one channel through which government can capture cost savings and efficiency improvements generated by Medicare Advantage plans.

One additional element of MA plan payments is risk adjustment at the individual level. One motivation for risk adjustment, even early on in the MA program, was an anticipation that MA would attract relatively

programs. Interested readers can read [Curto \(2023\)](#) for more discussion of Medigap pricing policies.

⁴Some beneficiaries have the additional option to enroll in an exclusive group MA plan that is sponsored by their former employer. We exclude these enrollees from our analysis.

healthier beneficiaries than FFS ([McGuire et al. 2011](#)). Hence, absent risk adjustment, CMS would be overpaying plans for these beneficiaries relative to the cost of insuring those beneficiaries under FFS.

For each Medicare beneficiary, CMS constructs a risk score r based on a beneficiary's age, gender, and chronic conditions. Specifically, diagnoses are grouped into Hierarchical Condition Categories (HCCs). Each HCC for which a beneficiary had a corresponding condition raises their risk score by a pre-specified amount.⁵ With these risk scores constructed, the base per-enrollee payment to MA plans is $rb - \max\{0, b - B\}$. That is, CMS pays plans their bid, risk adjusted for each individual beneficiary, net of the basic premium paid by enrollees themselves. The rebate payment is risk adjusted in the same way.

1.3 Plan Design

MA insurers can offer a broad and differentiated set of plan offerings, to appeal to the preferences of specific enrollees. At the same time, each MA plan must satisfy a set of basic requirements: plans must cover any service deemed by CMS to be “medically necessary,” and must offer cost-sharing at least as generous as offered by FFS for coverage of any in-network medical provider.

The main two types of MA plans are health maintenance organizations (HMOs) and preferred-provider organizations (PPOs).⁶ Both types of plans designate a limit set of preferred providers as in-network. Enrollees receive more generous insurance coverage for seeing an in-network provider. In turn, as in other health insurance markets, plans can, in theory, use network restrictions to negotiate price concessions from in-network providers. Unlike in other contexts, however, CMS requires that out-of-network providers must be paid FFS reimbursement rates by MA plans by default. This pushes reimbursement rates in MA towards FFS rates. In practice, there is very little difference on average between MA and FFS reimbursement rates ([Curto et al. 2019](#)).

HMO plans differ from PPO plans by using additional utilization management tools. HMO plans mandate care coordination through the patient's (explicitly-designated) primary care provider, meaning that enrollees *must* obtain a referral before seeking specialty care. By virtue of this gatekeeping, HMOs enforce greater utilization management through policies like prior authorization than PPOs do. PPOs typically provide some limited coverage for services rendered by out-of-network providers, whereas many HMOs do not provide any such coverage.⁷

In exchange for these restrictions, MA plans offer a wide variety of supplemental benefits. MA plans significantly reduce patient cost-sharing relative to the standard FFS arrangement; [Ippolito et al. \(2024\)](#) estimate that out-of-pocket costs are 18-24% lower in MA than in FFS. Plans also offer ancillary benefits, including coverage for vision, dental care, and gym memberships. Finally, MA plans can offer reduced premiums and cost-sharing for integrated Part D drug coverage. The base payments to plans are *only* meant to cover standard FFS medical coverage. Statutorily, plans must finance these supplemental benefits through

⁵CMS also deflates risk scores for MA enrollees by a fixed proportion, currently 5.91%, to account for expected coding differences between MA plans and FFS.

⁶PPOs are typically categorized as “local” or “regional” based on the geographic footprint of their provider network. A third type of plan, private fee-for-service plans, was dominant in the MA market in earlier years but commands virtually no market share during our period of analysis.

⁷Point-of-service or HMOPOS plans (which we categorize as HMOs) do, however, provide some out-of-network coverage and occasionally allow the patient to bypass their primary care provider.

either the rebate (of which 100% of dollars must, actuarially, be spent on these benefits) or through a supplemental premium charged to enrollees. In 2019, 51% of rebate dollars were spent on cost-sharing reductions, 16% were spent on premium reductions, and 33% on other supplemental benefits ([MedPAC 2021](#)).

2 Data and Sample

2.1 Data Sources

Our primary data comes from two sources: Inovalon and CMS. From both datasets, we obtain health insurance enrollment and claims data covering the years 2012-2021. We exclude 2020 and 2021 to avoid the COVID-19 pandemic, an unusual circumstance under which the effects of MA may have differed in a way that is likely incomparable to ‘normal times.’

The MORE² Registry from Inovalon contains claims data from a significant share of the nation’s insurers. Inovalon receives medical and prescription drug claims data from their insurer clients to support quality- and risk-related analytics. The dataset is therefore effectively sampled at the insurer-state-year level, covering the near-universe of enrollees in those insurers’ plans.⁸ This includes all commercial health insurance market segments, such as employer-sponsored insurance and the individual exchanges, along with hybrid public-private segments such as Medicare Advantage and Medicaid Managed Care. We only retain the employer-sponsored and Medicare Advantage segments, and exclude Medicaid and the individual exchanges from our analyses. Our final dataset covers a little over 50 unique carriers both in ESHI and MA. At any given point in time during our study period, the Inovalon data covered about 30% of the commercially-insured population. Uniquely relative to other commonly-used datasets covering the commercially-insured, the Inovalon data contain encrypted individual identifiers (including full name, exact date of birth, gender, and address) that can be used for external data linkage. The primary weakness of the Inovalon data is that we very rarely observe payment information on claims. Therefore, for all claims in our dataset (both MA and FFS, whether or not we observe payment amounts), we impute the average reimbursement rate for the associated service paid under FFS.

We use CMS data from the Qualified Entity program. The CMS data track enrollment and demographics information for 100% of beneficiaries of the Medicare program (including MA beneficiaries), on attributes such as ZIP Code, age, gender, race. This contrasts with the Inovalon data, which does not have any enrollment or demographic information on the FFS population, and only tracks this information for the subset of MA beneficiaries for which it has claims. Additionally, the CMS data includes claims files tracking all utilization for Medicare FFS beneficiaries. Importantly, the Qualified Entity data also include individual beneficiary identifiers that can be used for external data linkage.

Since both datasets contain the same types of direct person-level identifiers, individuals in both datasets can be linked deterministically. We undertake this linkage using a combination of unique identifiers, including Social Security number, gender, and date of birth. Use of this combination of very specific identifiers ensures validity and minimizes the likelihood of erroneous linkages. We limit just to individuals who are

⁸Due to privacy restrictions, the final dataset we use does not include the names of the insurance carriers, nor those of their plans. Inovalon allowed us to link plan characteristics (described below) *before* the plan de-identification process.

successfully linked across the two datasets, who appear in both the CMS Medicare enrollment files (covering MA and FFS) and the Inovalon commercial enrollment files.

We supplement our main claims and enrollment data sources with a handful of additional datasets. To measure socioeconomic characteristics, we use data from Acxiom, which tracks these at the 9-digit ZIP Code level. Specifically, we merge in ZIP-9-level socioeconomic measures, including share of residents who completed high school, average household income, average household net worth, and unemployment rates. We additionally merge in public CMS data on plan characteristics and plan-level MA bid and rebate amounts, as well as county-level benchmark payment amounts. Due to privacy concerns, the final analytic dataset does not include identifiers (not even anonymized) for counties or plans. To preclude potential re-identification of individual counties and plans, we are only able to observe ventile intervals of bid, rebate, and benchmark amounts; when we use those variables for each county/plan we substitute the mean value of the associated ventile.

2.2 Analytic Sample

We focus on Medicare beneficiaries who newly qualify for the program when they turn 65. Our research design, as described in Section 3.1, requires us to have data from beneficiaries when they are enrolled in the Medicare program (either in FFS or MA), as well as preceding Medicare enrollment, making this period best suited for estimated treatment effects of MA enrollment.

We therefore restrict our sample to only those individuals who turn 65 between the years 2015-2018, for whom we can potentially observe data both before and after Medicare enrollment. We further restrict to those who were fully enrolled in Medicare—in all three of Parts A, B, and D—within 3 months of turning 65, and who furthermore remained in Medicare for all 12 months following initial enrollment. We additionally restrict to those who were not simultaneously enrolled in either Medicaid or commercial coverage, throughout all 12 months following their enrollment in Medicare. We restrict to those who were under commercial coverage all 12 months prior to enrollment in Medicare, in a commercial plan that was tracked in the Inovalon data for that time period. Specifically, we restrict to plans for which Inovalon has both medical and prescription drug claims data. For those who enroll in Medicare Advantage, we additionally restrict to those in MA plans tracked in the Inovalon data, and limit to MA plans that have a carved-in prescription drug benefit (MA-PD plans). Finally, we remove those who enroll in an Employer Group Waiver Plan (EGWP) under MA, under which their former employer or labor union subsidizes enrollment in an MA plan as a fringe benefit. We do so since these plans have a substantially different financing structure, thus making our fiscal analysis in Section 4 more difficult to conceptualize.

We define MA enrollment status, and whether individuals get categorized as being in the MA or FFS cohort, based on individuals' MA enrollment status within one month of Medicare enrollment. For both the MA and FFS cohorts, we restrict to individuals who remained in their initial program selection for all 12 months following Medicare enrollment, and exclude those who switched between the programs during that time period.⁹

⁹In other analyses, we consider subsamples for which we can extend our analysis further in time before or after Medicare enrollment. To do this we simply take subsamples from our base analytic sample. This is described further in Appendix B.

Between 2012-2019, about 1.3 million individuals were enrolled in the Medicare program at age 65, with 56% of them enrolled in MA. After our sample restrictions, our final sample composes of 205,557; 180,087 (87%) enrolling in FFS, and 25,470 (13%) enrolling in MA. Of the restrictions we impose, the ones that reduce our sample the most are a) the restriction to 2015-2018; b) the requirement for at least 12 months of coverage in the Inovalon data at age 64; c) no concurrent enrollment in commercial coverage at age 65; d) enrollment in a non-EGWP plan; and e) tracking of MA claims within the Inovalon dataset. In contrast, the requirements that enrollees stay in their plans continuously; that Inovalon tracks their commercial plans well; and that they enroll at age 65 do not bind as tightly. The final two requirements (that MA claims must be tracked, and that enrollees must be in non-EGWP plans) is especially binding for the MA component of our sample, resulting in MA underrepresentation within our sample; in contrast, we observe the universe of claims for FFS enrollees. We provide a step-by-step evolution of how our sample changes as we add restrictions in Appendix Table A1.

MA enrollees in our sample are slightly more likely to be non-white and to live in an urban county than FFS enrollees, and live in neighborhoods with somewhat lower average income. They are much more likely to have been enrolled in an HMO plan at age 64, which may reflect their comfort with managed care. Finally, they have much lower risk scores and utilization at age 64, reflecting MA's relative appeal to lower-risk enrollees. We plot these summary statistics in Table 1.

The extent to which our sample is broadly representative depends on the geographic coverage of the Inovalon data. This is determined by which insurer clients they have contracted with. In Appendix Figure A1, we plot the relative geographic distribution of our analytic sample. We are able to track MA enrollees in 32 states. Our MA coverage is especially dense in the Northeast and Great Lakes regions of the US. On the other hand, we have very little coverage in the Great Plains and Deep South. Our FFS coverage is closer to proportional relative to state populations.

How does our sample compare to a broader population? We make two comparisons. First, we can compare MA enrollees in our analytic sample to MA enrollees who we can track at age 64, when they are enrolled in an Inovalon client ESHI plan, but *not* age 65, since they enroll in MA plans that are not Inovalon clients. This group is largely similar to MA enrollees in our analytic sample, except they are somewhat less likely to be white (84% compared to 91% in our analytic sample) and have lower average quarterly spending at age 64 (\$1,175 vs. \$1,464). We display this comparison in Table 1. Second, we can compare to a broader population of 65-year-old MA/FFS enrollees represented in the Medicare Beneficiary Summary File. We cannot link this group to Inovalon data, meaning we do not have fine-grained socioeconomic data, and must instead use characteristics at the county level rather than the 9-digit zip code level. Largely due to our limited geographic coverage, beneficiaries in our dataset are much more likely to be white, and live in areas with higher average income and higher home ownership rates. We display this comparison in Appendix Table A2.

A more substantive limitation of our dataset (motivated by our empirical approach, described in the next section) is that we only observe new 65-year-old Medicare beneficiaries, who are young relative to the average beneficiary who qualifies by age. This limitation, as well as the other limitations discussed above, limit the generalizability of our estimates; however, they allow us to discuss the role of selection bias in estimates of MA treatment effects.

3 Effects of Medicare Advantage on Enrollee Outcomes

We begin by estimating the causal effect of enrollment in MA (relative to enrollment in FFS) on utilization and care quality outcomes for Medicare beneficiaries.

3.1 Research Design

Our goal is to estimate the impacts of the MA program; that is, if the MA program were to not exist, how would outcomes change? Therefore, our target estimand is the average treatment effect on the treated (ATT). That is, the average treatment effect of MA on outcomes, relative to FFS, averaged over those who empirically choose to enroll in MA.

Consider $Y_i(T)$, the potential outcome for an individual i if they were enrolled in insurance option T , and the binary variable MA_i as defining whether i enrolled in MA upon entering the Medicare program. The ATT is defined as:

$$ATT = \underbrace{E[Y_i(MA)|MA_i = 1]}_{\text{Avg. outcome for MA enrollees}} - \underbrace{E[Y_i(FFS)|MA_i = 1]}_{\text{Avg. outcome for MA enrollees if they were enrolled in FFS}}$$

i.e., the difference in expected outcomes for MA enrollees under MA, compared to expected outcomes under FFS. Unfortunately, the ATT cannot be directly observed, since $E[Y_i(FFS)|MA_i = 1]$ is a counterfactual object; we cannot observe outcomes under FFS for any MA enrollee. A feasibly observable object is the difference in means between MA enrollees and FFS enrollees at age 65, D . Such a difference would estimate:

$$\begin{aligned} E[D] &= \underbrace{E[Y_i(MA)|MA_i = 1]}_{\text{Avg. outcome for MA enrollees}} - \underbrace{E[Y_i(FFS)|MA_i = 0]}_{\text{Avg. outcome for FFS enrollees}} \\ &= ATT + \underbrace{E[Y_i(FFS)|MA_i = 1] - E[Y_i(FFS)|MA_i = 0]}_{\text{Selection bias}} \end{aligned}$$

The observed difference between MA and FFS enrollees is a biased estimator of the ATT, with bias coming from the fact that there may be selection into FFS vs. MA based on underlying health characteristics, which also affect (counterfactual) outcomes under FFS enrollment.

If we observe individual-level characteristics X_i (such as demographics or health status), then, under the assumption that $Y_i(FFS) \perp\!\!\!\perp MA_i|X_i$, we can estimate the difference D while controlling for (or reweighting/matching by) X_i . If there are no factors that influence both outcomes and FFS/MA choice that are not included in X_i , then the resulting estimate will be purged of selection bias ([Landon et al. 2012, 2015](#), [Curto et al. 2019](#), [Jung et al. forthcoming](#)). This has two challenges: first, a major factor influencing outcomes such as utilization is patient health, which is a high-dimensional object. Researchers typically must instead condition on a low-dimensional representation (e.g., a risk score), which may not perfectly capture all important facets of health, leaving room open for selection bias. Second, if observable characteristics are reported differently in MA vs. FFS ([Geruso and Layton 2020](#)), then enrollees who are

identical on measured characteristics may not be identical on true characteristics, generating bias.

We take a different tack. We note that, in our sample, we can observe outcomes for both MA and FFS enrollees *before* they turn 65, when both are enrolled in employer-sponsored health insurance (ESHI). Therefore, we can estimate

$$E[D^{ESHI}] = \underbrace{E[Y_i(ESHI)|MA_i = 1]}_{\text{Avg. outcome for future MA enrollees when they were enrolled in ESHI}} - \underbrace{E[Y_i(ESHI)|MA_i = 0]}_{\text{Avg. outcome for future FFS enrollees when they were enrolled in ESHI}}$$

the difference in outcomes between *future* FFS enrollees and *future* MA enrollees at age 64. Since both groups are enrolled in ESHI coverage in this period, differences between them cannot reflect the treatment effect of MA, and instead only reflect underlying differences in their propensity to use care.

To the extent that $E[D^{ESHI}]$ is equal to the selection bias arising from simple comparisons between MA and FFS enrollees, subtracting it out allows us to estimate an unbiased treatment effect. More formally, if $E[D^{ESHI}] \approx E[Y_i(FFS)|MA_i = 1] - E[Y_i(FFS)|MA_i = 0]$, then

$$\begin{aligned} E[D] - E[D^{ESHI}] &= \underbrace{E[Y_i(MA)|MA_i = 1] - E[Y_i(FFS)|MA_i = 0]}_{\text{Observed post-enrollment differences}} \\ &\quad - \underbrace{E[Y_i(ESHI)|MA_i = 1] - E[Y_i(ESHI)|MA_i = 0]}_{\text{Observed pre-enrollment differences}} \\ &\approx E[Y_i(MA)|MA_i = 1] - E[Y_i(FFS)|MA_i = 0] \\ &\quad - E[Y_i(FFS)|MA_i = 1] - E[Y_i(FFS)|MA_i = 0] \\ &= ATT \end{aligned}$$

This suggests that a simple difference-in-differences estimator, comparing eventual MA vs. eventual FFS enrollees before and after they enter Medicare, will unbiasedly estimate the ATT.

The core assumption behind this strategy is that differences in observed outcomes under ESHI coverage are equal to differences in potential outcomes under FFS. This embeds two core assumptions. First, as with all difference-in-differences research designs, we must assume parallel counterfactual trends in outcomes between the treated and untreated individuals. In our context, this is equivalent to assuming that individuals do not sort into MA or FFS based on how they expect their outcomes to *change* if they were to transition from ESHI to FFS, so differences measured at 64 reflect permanent latent gaps between the groups. Formally, we assume that $Y_i(FFS) \perp\!\!\!\perp MA_i|Y_i(ESHI)$ at age 65.

The largest threat to this assumption is the (implicit) functional form assumption that must be made: We must assume that *level* differences under ESHI are equivalent to counterfactual level differences under FFS, in order to unbiasedly estimate the ATT. If, for instance, utilization is *multiplicative* in arguments and (as we show later in this section) FFS raises utilization relative to ESHI, counterfactual level differences under FFS may be larger than observed level differences under ESHI. In this case, our estimates should be thought of as upper bounds on the true treatment effect of MA.¹⁰ In contrast, we do not face any threat to identification

¹⁰Below, we show that utilization under ESHI is similar to utilization under MA. If this is the case, our coefficients will instead estimate the average treatment effect on the *untreated* (ATT). The ATT is equal to the ATT so long as there is no selection into

from behaviors such as intertemporal substitution—i.e., individuals delaying care until they turn 65 to take advantage of more generous Medicare coverage—as long as this behavior is identical across future MA and FFS enrollees.

The other assumption we must make is that differences in outcomes under ESHI coverage reflect *only* underlying population differences. The main threat to this assumption is that ESHI coverage is not a uniformly-defined treatment. An ESHI enrollee’s outcomes will partially reflect the characteristics of the plan they are enrolled in. This will be a threat to identification if an individual’s ESHI plan is related to their choice of whether to enroll in MA or FFS. A plausible channel is that, as described in Section 2.2, individuals enrolled in ESHI HMO plans are more likely to opt into MA, and may have lower utilization under ESHI due to the HMO plan’s restrictions.

Our approach is to handle this potential threat through matching. Ideally, we could match MA enrollees to FFS enrollees who were enrolled in identical ESHI plans at 64. However, we are only able to observe plan type (e.g. HMO/PPO) at age 64, and, due to the fact that we rarely observe payment fields, cannot impute cost-sharing rules for most of our sample. Therefore, we match exactly on plan type, which we do observe, and assume that, conditional on observables at 64, the ESHI plans that eventual MA enrollees are in are similar to those of eventual FFS enrollees. We think this is more plausible assumption than, e.g., assuming the same for the choice of MA vs. FFS, since ESHI plans are, in large part, chosen by an employer rather than by the individual themselves. We perform matching in two steps: First, for each MA enrollee, we construct a group of match candidates in the exact same cohort (same month of birth, state of residence, and urban status)¹¹ who are enrolled in the same type of ESHI plan at age 64 (HMO or PPO). We then estimate a model of individuals’ propensities to enroll in MA. We assume that the probability of enrollment is $Pr[MA_i|X_i] = \frac{\exp(\delta X_i)}{1+\exp(\delta X_i)}$, where X_i includes the factors exactly matched on above, gender, race, health characteristics for both risk adjustment factor (RAF) and hierarchical condition categories (HCC) at 64, and average income and net worth in the individual’s 9-digit ZIP Code. We then match each MA enrollee to the five FFS enrollees who were valid controls with the closest propensity scores, with replacement. In the third and fourth columns of Table 1, we report summary statistics on the matched sample. Our matching approach improves balance in terms of observables between MA and FFS enrollees, including unused variables such as utilization and risk scores at 64.

The extent to which selection bias remains results in our estimates being either upper or lower bounds of the true causal effect of MA enrollment, depending on the sign of the residual selection. To the extent that pre-Medicare utilization is only partially able to control for favorable selection (i.e., if MA plans are still favorably selected even conditional on this utilization), our estimates will be upper bounds, and the true effect of MA will be smaller.

Our primary specification is a matched and stacked difference-in-differences estimator (Brot et al. 2024).

MA based on its potential (individual-specific) treatment effects. Such an assumption is somewhat implausible given that we find later that a major selection margin is to avoid managed care, potentially implying that those who select into MA expect to be less affected by managed care. However, there are reports that some MA enrollees were unaware of what they were signing up for, sometimes being unaware that they were enrolling in MA at all (Abelson and Sanger-Katz 2022), potentially blunting any such precise selection on treatment effects. In the next section, we estimate treatment effects under an alternative parallel trends assumption for robustness.

¹¹We match exactly on cohort to account for potential differences at age 64 arising from supply-side differences in medical practices across space and time.

The regression form of this estimator is

$$Y_{it} = \beta(MA_i \times Post_t) + \lambda_i + \eta_{g(i)t} + \epsilon_{it} \quad (1)$$

where β is the target parameter, a coefficient on the variable $MA_i \times Post_t$ that indicates where beneficiary i was enrolled in MA in time t . We include individual fixed effects λ_i , and match-group-by-time fixed effects $\eta_{g(i)t}$. By including the latter set, our estimator becomes a simple average of within-match-group difference-in-differences estimators. To ensure that each within-match-group estimator is comparable (estimating the effects of MA in the first year of enrollment), we limit our data to only include, for each individual, 4 quarters before the individual turns 65, and 4 quarters after. This approach allows us to enforce which sorts of pairwise comparisons are allowed to enter our estimator, given a recent literature on how standard approaches to staggered difference-in-difference research designs may permit undesirable pairwise comparisons to influence the estimator (Roth et al. 2022). In all regressions, we cluster standard errors at the individual level.

3.2 Utilization Effects

The empirical strategy detailed above allows us to estimate the effect of MA on health care utilization. Economists generally measure utilization across all services in terms of total allowed spending. As described in Section 2.1, however, we impute all prices at their FFS levels. Therefore all differences in spending between FFS, MA, and ESHI reflect *only* quantities of services consumed, and *not* differences in prices.

We begin by presenting raw time series plots of overall medical utilization, using our above measure, by MA and FFS enrollees in Figure 1. In the year after enrolling in Medicare, MA enrollees use substantially less care than FFS enrollees, as has been previously documented. This difference, however, might reflect the treatment effect of MA *or* differential selection. In the year before enrolling in Medicare, MA enrollees also have lower utilization, but to a much smaller extent.¹² That there is a difference at age 64 suggests that part of the post-65 difference is explained by selection, but the fact that the pre-65 gap is smaller than the post-65 gap suggests some of the post-65 gap comes from MA treatment effects. Interestingly, MA appears to hold beneficiaries at close to their ESHI utilization levels, whereas utilization increases substantially following enrollment in FFS.

We quantify the treatment effect of MA by estimating a series of regressions below, with the estimated treatment effects listed in Table 2. We first simply regress utilization on an indicator for MA enrollment and quarter fixed effects, only looking at enrollees at age 65, when they are enrolled in the Medicare program. This gives us the raw difference in utilization between the two groups as portrayed in Figure 1. MA enrollees use 29.6% less care (\$650 per beneficiary-quarter) than FFS enrollees.

From this starting point, we move towards empirical approaches that control for potential selection. We next estimate (in column 2) a more typical approach in the existing literature, where we control for rich observable factors: Fixed effects for cohort, state, race, gender, whether the individual lives in an urban area, and indicators for the presence of a chronic condition within each Hierarchical Condition Category

¹²While there is a dip in utilization in the quarter before turning 65—likely due to patients deferring care to take advantage of lower expected prices under Medicare—event study estimates suggest this dip is roughly identical between the two groups.

(HCC).¹³ Under this standard risk adjustment approach, we find that MA reduces utilization by 19.3%. These estimates are of comparable magnitude to prior studies using such methodologies, which usually find that MA enrollees use 15-40% less care than FFS enrollees after standard risk adjustment ([Landon et al. 2012, 2015, 2023, Curto et al. 2019, Jung et al. forthcoming](#)). Adding matching on top of these controls does little to influence the estimates.

Finally, we add in data from age 64, and allow for fixed effects for both MA_i and $MA_i \times Post_t$, the differences at ages 64 and 65, respectively. This effectively controls for any pre-existing differences in MA and FFS enrollees' outcomes from prior to Medicare enrollment, based on utilization at age 64. When we move to this design, our estimate of the treatment effect of MA drops substantially, to 8.3%, suggesting that the observables used in the preceding specification did not fully account for pre-existing differences between MA and FFS. After including individual fixed effects and matching, in line with our primary specification described in Section 3.1, our final estimate is that MA enrollment reduces utilization by 6.2%, or \$125 per beneficiary-quarter. Most of this change comes from individual fixed effects; the fact that matching only reduces our estimates by 0.5pp reassures us that the threat to identification due to differences in ESHI plans at age 64 is likely to be minor.

In Figure 2 (in the red line), we plot quarter-by-quarter event study estimates from our primary specification. Reassuringly, estimated differences between MA and FFS enrollees are roughly flat while both are age 64. When both turn 65 and enroll in either MA or FFS, we see that the estimated difference between the MA and FFS cohorts turns sharply negative, consistent with our main result and time series plots described above.

One weakness of our sample is that we only measure utilization for a limited time period, both before and after beneficiaries' Medicare enrollment. This poses two potential problems: First, our ability to diagnose differential pre-enrollment trends is limited by our ability to observe more pre-enrollment years. Second, our primary estimates focus on treatment effects at age 65; treatment effects may be larger or smaller in older ages. We therefore redo our analysis with longer panels. Doing so requires limiting our sample to a smaller number of beneficiaries. For example, since our data coverage ends in 2019, we cannot estimate effects in the full second year of enrollment more than one year post-enrollment for any beneficiary who turned 65 later than January 2018. Similarly, there are some individuals whose commercial claims were not tracked more than one year before their Medicare enrollment, either due to their last commercial insurer not having yet become an Inovalon client, or them having previously switched insurers from a non-Inovalon to Inovalon client.

We therefore re-perform some of our analyses on various subsamples where we observe 1-3 years before enrollment, and 1-3 years after enrollment. For each panel window, we limit to a balanced panel of individuals within the specified period, and rematch within this subsample. We describe our full procedure more thoroughly in Appendix B. Appendix Table B1 reports summary statistics for samples with different panel length. Qualitatively, this subsampling does not introduce any major additional differences between the MA and FFS groups, except that samples with more pre-65 years contain somewhat less individuals enrolled in

¹³We measure chronic conditions at age 64, for two reasons. First, if MA plans upcode, these chronic conditions will reflect beneficiary health differently for MA and FFS enrollees. Second, the Inovalon and CMS datasets appear to code diagnoses at different frequencies per claim, so we empirically observe more diagnoses for FFS enrollees at age 65 than MA enrollees.

HMOs at 64. Using longer panels, particularly when we add more pre-enrollment years, drops our sample substantially.

In Appendix Table B2, we consider estimates from our primary specification for these subsamples. First, we consider using longer pre-enrollment windows. Doing so allows us to use more information—utilization in any given (pre-Medicare) year contains both information about underlying differences *and* statistical noise; in contrast, using more years reduces this noise. Estimates with longer pre-enrollment windows are somewhat larger; using 2 pre-enrollment years produces causal MA utilization reduction estimates of 7.7%, and using 3 years produces estimates of 9.3%. However, as Figure 2 shows (in blue), pre-enrollment trends are still parallel (for the 2 year pre-/post-enrollment subsample) even for this subsample; they also track the 1-year pre-enrollment trends of the full analytic sample.

Second, we consider using longer post-enrollment windows, to track how the effects of MA change over time. We estimate larger effects in the second year of enrollment: MA reduces utilization by 9.0-17.2% across specifications, compared to reductions of 4.2-5.7% in the first year under the same specifications. In the specification where we use three post-enrollment years, MA reduces utilization by 18.6% in the third year, compared to 4.2% in the first year and 9.0% in the second. As demonstrated in Appendix Figure B1, the increasing effects of MA over time come from FFS enrollees increasing their utilization over time while MA enrollees' utilization remains stable. Though the estimates rise substantially, the standard errors do as well (especially for our sample with two years of pre- and post-enrollment data), and so we cannot always reject that estimates have not increased across post-enrollment years.

We also explore robustness to alternative functional form assumptions. As we discuss in the prior section, we must assume that differences at age 64 in ESHI are equal to counterfactual differences in FFS. One reason that might not be true is that utilization is higher in FFS than in ESHI for FFS enrollees. If differences across individuals in spending are from factors that are *multiplicatively* separable rather than additively separable, differences at ESHI will be underestimates of selection bias. We therefore consider estimation of effects on utilization under an alternative assumption: that, if we forced both groups into FFS, the *ratios* of average spending between FFS and MA enrollees would be the same as they are when both groups are enrolled in ESHI at age 64; i.e., that $\frac{E[Y_i(ESH)]|MA_i=1}{E[Y_i(ESH)]|MA_i=0} = \frac{E[Y_i(FFS)]|MA_i=1}{E[Y_i(FFS)]|MA_i=0}$. We can then estimate multiplicative treatment effects as $\frac{\frac{E[Y_i(MA)]|MA_i=1}{E[Y_i(FFS)]|MA_i=0}}{\frac{E[Y_i(ESH)]|MA_i=1}{E[Y_i(ESH)]|MA_i=0}}$ using Poisson regression (Wooldridge 1999, 2023), which are comparable to our estimates of percent changes in our main specification. We run specifications with and without using age 64 data, and with and without matching.¹⁴ Our estimates (shown in Appendix Table A3) of the risk-adjusted difference under this specification are much larger (estimated reductions of 23.0% and 26.2% compared to OLS estimates of 17.7% and 19.3%), but our difference-in-differences specifications are comparable (estimated reductions of 9.6% and 6.3% compared to OLS estimates of 8.3% and 7.5%), suggesting that our specific parallel trends assumption is unlikely to have significant influence on our estimates.

We also estimate our results under alternative matching strategies. In the first, we match *without* replacement (in contrast with our primary approach, which matches with replacement) to avoid repeatedly

¹⁴Note that we cannot run our primary specification since it would require estimating a maximum likelihood specification with many (beneficiary-level) fixed effects, and our server access did not allow us to add software to do so easily.

sampling the same FFS beneficiaries. Our estimates (shown in Appendix Table A4) under this approach are only slightly larger (7.5% compared to 6.2% in our main specification).

3.3 Heterogeneity in Utilization Effects

A natural question is what care is being reduced by MA, and how these reductions are achieved. In Figure 3, we begin to explore the drivers of this utilization reduction by looking at differential MA impacts by type of utilization. We use our primary specification, with two outcomes: Quarterly utilization of a given service type, and a binary indicator for whether the beneficiary ever used a service of that type in a given quarter.

We find that MA reduces the use of inpatient services tremendously, with utilization reduced by 24.2% and extensive margin use reduced by 29.2% relative to FFS.¹⁵ The reduction in inpatient use is the primary driver of MA's savings: Of the \$125 per enrollee-quarter reduction we estimate, \$100 comes from inpatient spending.¹⁶ In contrast, there are modest reductions in use but modest increases in spending for outpatient service categories. Additionally, we estimate slight increases in utilization of prescription drugs, which is to be expected given that drug benefits in integrated MA plans tend to be more generous than benefits in the standalone Part D plans used by FFS enrollees ([Starc and Town 2020](#)).

Finally, we estimate very large reductions in spending on post-acute care, though much smaller reductions in extensive margin use. Post-acute care is thought to be a significant driver of waste in the Medicare program ([Doyle et al. 2017](#), [Einav et al. 2023](#)). That we find large reductions in spending but small reductions in use on the extensive margin suggests that MA plans are able to shorten spells of care at these facilities. Prior research has shown that FFS reimbursement policies incentivize post-acute care facilities to keep patients too long ([Einav et al. 2018](#), [Eliason et al. 2018](#)). Our results may be a ramification of MA plans using reimbursement arrangements that are less amenable to gaming.

We also study whether MA reduces utilization for certain types of beneficiaries more than others. We estimate the impact of MA separately for different treated subgroups. In doing so, we condition only on the characteristics of MA enrollees, and retain their full match group regardless of whether each member of that group has the same characteristics, to retain comparability to our main estimates. For instance, when estimating effects for women, we only include female MA enrollees, but they may be matched to male FFS enrollees.¹⁷

We estimate heterogeneous treatment effects by gender, race (white vs. non-white), quartiles of income (as measured by the median income in the beneficiary's 9-digit ZIP Code), and terciles of health status (as measured by their HCC-based risk score constructed at age 64). We plot these treatment effects, in terms of the percent change in utilization induced by MA enrollment, in Figure 4. There is little difference in effects by gender. However, there are large differences by race, with non-white beneficiaries having much

¹⁵These estimates are less than half the size of effects on inpatient use estimated by [Duggan et al. \(2018\)](#), who study those who switch from MA to FFS due to their MA plan's dissolution.

¹⁶One worry is that our estimates are excessively high if MA plans reclassify inpatient admissions as observation stays. We might expect them to do so given that inpatient admissions count towards certain quality measures but observation stays do not. However, we find that extensive margin use of observation stays declines by the same magnitude as inpatient visits, suggesting that these reporting issues are not driving our results.

¹⁷Enforcing characteristic restrictions on FFS enrollees results in nearly identical point estimates, though with larger standard errors due to the reduced sample size.

larger reductions under MA than white beneficiaries, though we cannot statistically reject equality between groups. Similarly, there is a sharp gradient in effects by income, with those in the bottom half of the income distribution seeing sharp utilization reductions, while MA appears to increase utilization among the highest quartile, though we cannot reject zero effects for the latter group. Most starkly, the effects of MA are strongly heterogeneous across risk score. MA increases utilization by the healthiest tercile of enrollees, has approximately zero effect on the middle tercile, and sharply reduces utilization for the sickest tercile. This is consistent with the fact that MA savings are from inpatient facility use, which is primarily used by the sickest beneficiaries, whereas MA plans are generally more generous than FFS, which might bolster utilization among the healthy.

In Appendix Figure A2, we pool MA enrollees by their propensity score, binned into quartiles. We reuse the propensity score used for matching. These estimates tell us to what extent treatment effects vary across beneficiaries given their likelihood of enrolling in MA in the first place. We estimate that beneficiaries who are least likely to enroll in MA experience *increases* in their utilization as a result of MA enrollment, though we cannot statistically reject null effects. In contrast, the largest reductions in utilization come from those who are the most likely to enroll. Those who enroll despite having low expected propensity to do so must have unusually strong preferences for MA. Therefore, enrollees with lower propensity scores must have higher unobserved preferences for enrolling in MA. We thus interpret these results as suggesting that treatment effects are lower for those with stronger unobserved preferences. That is, beneficiaries are more likely to enroll in MA if their individual treatment effects are smaller.

MA plans reduce utilization, despite the fact that enrollees, on average, face *less* cost-sharing than would if enrolled in FFS. How, then, do MA plans achieve these reductions? The primary way in which MA plans differ from FFS is in their use of managed care policies. It would be ideal to measure to what extent managed care explains the difference between MA and FFS. The use of such policies is highly multidimensional, however—MA plans face many binary decisions of, for example whether to keep each hospitals in- or out-of-network. Moreover, CMS does not record all of these plan design choices in a systematic way. To test the role of managed care, we compare the two types of MA plans: HMOs and PPOs. As we described in Section 1.3, both plans employ the use of network limitations, but HMOs provide no coverage for out-of-network providers, while also employing additional authorization restrictions on coverage of specialist services.

We only find a statistically significant reduction in utilization for HMO plans; this reduction amounts to \$332 per beneficiary-quarter, or 16.6% of spending. In contrast, we estimate that MA PPO plans *increase* spending by \$102 per beneficiary-quarter, though we cannot statistically reject that they have no effect at all. This suggests that the impact of MA on utilization relative to FFS is primarily the impact of managed care restrictions. To the extent that PPOs increase utilization despite having some use of managed care, this is likely to come from the fact that cost-sharing faced by MA enrollees is, on average, more generous than FFS enrollees.

We plot this result, along with heterogeneity by other features of MA plans and the markets they operate in, in Figure 5. Other than the HMO/PPO distinction highlighted above, we cannot statistically reject equality in effects across plans with different star ratings, as well as across markets with more or less concentration of plan market shares, and across markets with greater or lesser MA penetration rates.

Selection into HMO plans, relative to PPOs, is quite heterogeneous. Can heterogeneous selection explain

our results above? In Appendix Figures A3 and A4 we replicate Figures 3 and 4 separately for HMO and PPO enrollees. A surprisingly large extent of our heterogeneity is explained by differential selection into HMOs and heterogeneous HMO vs. PPO effects. For example, while, in aggregate, we find larger effects for non-white beneficiaries than white beneficiaries, we find equally large effects for non-white *HMO enrollees* as white HMO enrollees. However, 87% of non-white MA enrollees choose an HMO plan, whereas 63% of white MA enrollees choose an HMO plan, thus explaining some part of the aggregate difference. We find similar patterns (though less stark) explain our estimates of heterogeneity by neighborhood income. Finally, the heterogeneity we observe by risk score is explained by HMOs strongly reducing utilization among those with the highest risk scores, while PPOs increase use among those with the lowest risk scores (with close to zero effects for HMOs on the low-risk and PPOs on the high-risk).

Similarly, Figure 3, at first glance, suggests that MA plans might induce substitution between inpatient and outpatient care, since the former declines and the latter increases. However, while some of this substitution might exist, we see far less of it when we look within plan type. HMO plans generate very large reductions in inpatient spending (-46%) relative to FFS. However, they only have minimal effects on increasing outpatient spending (+3.6%). In contrast, PPO plans generate larger increases in outpatient spending (+17%) and smaller decreases in inpatient spending (-15.3%) relative to FFS. Overall, while MA plans of all stripes generally tamper down inpatient spending relative to outpatient spending, HMOs have bigger overall effects on all categories, while PPOs significantly increase spending in some categories. This may be due to the fact that all MA plans have more generous cost-sharing relative to FFS; while HMO plans offset this with utilization management, PPO plans do not.

3.4 Quality Outcomes

MA's reductions in the use of care may increase social welfare if the foregone care is low value, but may decrease social welfare if the care is of high value. Previous studies have argued that MA reduces both high- and low-value care (Curto et al. 2019).

We construct measures used by the Agency for Healthcare Research and Quality's (AHRQ) Prevention Quality Indicator (PQI) system to measure the quality of care received. These indicators are meant to identify *consequences* of poor access to care, rather than the quantity of care per se. The specific outcomes we use are: rates of hospitalizations for preventable complications; 30-day readmission after an initial hospitalization; adherence to use of medication for hypertension, diabetes, or high cholesterol; high-risk medication use; initiation of treatment for alcohol or drug abuse; screening for breast cancer; and HbA1c testing for diabetes.¹⁸ Each of these measures either directly reflects low-value care, or complications from insufficient high-value care.

In Figure 6, we plot the estimated coefficients for each of these outcomes. We denominate the coefficients in percentage rather than absolute terms, for readability. Our results show MA substantially improves

¹⁸We measure readmissions unconditionally. That is, we include all beneficiaries in our sample, and construct an indicator for having an index admission *and* a readmission. We do this because MA may have a direct effect on the composition of beneficiaries who have initial hospitalizations. For example, if MA reduces low-value initial inpatient hospitalizations, its initially-hospitalized population will have a much higher, ex ante, likelihood of being readmitted, which would cause us to incorrectly estimate that MA increases readmissions even if it did not actually have such an effect.

care quality on some dimensions: it reduces preventable hospitalizations (by 24%), especially for acute conditions (by 59%), and reduces the use of high-risk medications (by 21%), despite the fact that MA otherwise increases overall prescription drug use. On the other hand, MA also generates modest reductions in breast cancer screening (by 8%) and diabetic hemoglobin testing (by 3%).

We additionally estimate the effect of MA on measures of quantity of high- and low-value care used in the prior literature ([Schwartz et al. 2014](#), [Brot-Goldberg et al. 2017](#), [Curto et al. 2019](#)). We report estimates in Appendix Figure A5. We find that MA increases use in all of our high-value care measures, though we are limited to measuring high-value care in terms of prescription drug use (including drugs for depression, diabetes, hypertension, and high cholesterol), which MA tends to increase in general. In contrast, we find mixed results for low-value care: MA plans reduce the use of some categories of low-value care, but increase the use of others.¹⁹

Our results contrast with those of [Curto et al. \(2019\)](#), who suggest that MA reduces both high- and low-value care in equal proportion. We instead find much more idiosyncratic results, in that MA plans greatly increase the use of some forms of high-value care, while reducing others, and reduce many forms of low-value care as well. We conclude that the utilization reductions achieved by MA plans do not appear to create unambiguous harms for enrollees; some enrollees may be harmed by MA enrollment, while others may benefit.

4 Effects of Medicare Advantage on Fiscal Costs

Our results above suggest that MA plans are able to reduce spending on insurance provision without clearly harming quality, and particularly seem to be cutting back on potentially low-value uses of care. Ideally, these spending reductions would be passed through to the federal government, allowing both parties to share the gains from privatization. However, federal budget analyses often conclude that MA *raises* fiscal costs substantially ([MedPAC 2025](#)). However, these analyses typically lack actual utilization data from MA and therefore generally use imputed values from FFS enrollees to calibrate how much MA enrollees would cost were they to be switched into FFS. Our combined dataset allows us to not only observe MA utilization, but also, as we already have done, directly estimate how utilization would change if beneficiaries were to move between the two programs. We now use those estimates to compute the fiscal consequences of MA for the Medicare program. We focus on the cost of providing insurance for medical services only, excluding prescription drug coverage, which is privatized for both FFS and MA enrollees.

4.1 Measuring Fiscal Costs

Our approach is to simulate costs under two scenarios: The first is the status quo, where some beneficiaries enroll in MA and some do not. Estimating this requires that we estimate current per-enrollee payments from CMS to MA plans. The second is a counterfactual scenario under which the MA program is completely discontinued, forcing MA enrollees into FFS.²⁰ This requires us to estimate what the costs to CMS would

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²⁰Another potential counterfactual scenario of interest would be if CMS were to discontinue the public FFS plan and force all beneficiaries to enroll in MA plans. In such a scenario, we would expect plan bids to change in response, and CMS would need to

be of directly insuring MA enrollees under the FFS program. We compute costs for each MA enrollee individually, which we can then aggregate in various ways.

To compute current payments, we replicate MA's capitation formula. Current payments have four components: First, base payments, which are the product of the plan's bid (up to the county benchmark), and the risk scores of beneficiaries the plan enrolls. We extract bids from publicly-reported bidding data, and compute the risk scores from our claims data at age 64. Second, rebate payments. As described in Section 1, if plans bid below the county benchmark, they receive a share of the difference as rebates to spend on supplemental benefits, paid for by CMS, which we can compute using the bid, benchmark, and risk score. We construct these using public reporting on base rebate amounts combined with the risk score estimates in our data. Third, quality bonus payments. Plans that have high star ratings receive a greater share of the bid-benchmark gap as rebates, and also face higher benchmarks, allowing them to receive greater payments for the same bid. We reconstruct this from the publicly reported quality scores and bids, along with the risk score estimates in our data. Finally, we account for upcoding. We measure all risk scores at age 64, before beneficiaries enroll in Medicare. However, it is known that risk scores for MA enrollees are elevated due to more frequent coding, as well as due to tools like health risk assessments and chart reviews that enhance diagnostic documentation, but do not appear in claims data ([Hammond et al. 2024](#), [MedPAC 2024](#)). We calibrate a multiplicative net upcoding factor by taking the difference between estimates of upcoding from [Geruso and Layton \(2020\)](#) relative to the upcoding adjustment used in the MA plan payment formula. We describe each of these procedures in more detail in Appendix C.

To compute CMS's counterfactual costs were they to ban MA, we inflate MA enrollees' average actual costs by the estimated yearly treatment effect of MA on utilization. We do this exercise only for medical utilization, excluding prescription drug use. This requires us to estimate effects for non-drug utilization; we report estimates of treatment in Appendix Tables C1 and C2. For any subsample, we use the treatment effect estimate for that subsample. We then convert spending into expected costs for CMS by excluding FFS's patient cost-sharing, and calibrating estimates of CMS's administrative costs per dollar of utilization, applied to our estimates of counterfactual FFS utilization.²¹

In Table 3, we present the breakdown of our approach to accounting for current and counterfactual costs, including all of the components described above. This table does so for all 65-year old MA enrollees in our sample. We estimate that the current cost of funding our sample of MA enrollees through the MA program is \$5,303 per beneficiary-year. In contrast, the cost of counterfactually insuring them through FFS would be \$4,597. This implies that MA raises the fiscal cost of Medicare by \$706 per beneficiary-year, 15.4% of counterfactual FFS costs.²²

MA enrollment reduces the use of care, but apparently raises fiscal costs of insurance provision. Why is find an alternative system to compute benchmarks without measuring spending of FFS enrollees. Since we do not have a complete model of plan bidding behavior, this simulation is left to future work.

²¹Note that, in this section, we are assuming that the only influence of the MA program is on MA enrollees. For instance, [Baicker et al. \(2013\)](#) find positive spillovers from MA onto FFS enrollees, and we will undercount these spillovers. Similarly, we will undervalue any extent to which the MA program puts pressure on providers or generates insurer participation in other related insurance markets.

²²In contrast, MedPAC's estimates for these years are that MA increases fiscal costs by 10-13% over this period, though they use a higher net upcoding factor than we do and consider all beneficiaries, rather than solely studying 65-year-olds ([Hammond et al. 2024](#)).

that? One reason is that, while this contrast does indeed estimate the general fiscal effects of MA, it does not necessarily reflect the relative efficiency of private vs. public provision. MA plans must offer, at a minimum, coverage that is at least as generous as FFS. In practice, they offer coverage which is more generous, in both financial terms (Ippolito et al. 2024) and in terms of supplemental benefit coverage. To consider relative efficiency, we would prefer an apples-to-apples measure of the cost of providing similar services.

To make such an apples-to-apples comparison, we ideally would want to break out the cost of providing these services. We do not, however, have accounting data that allows us to do this. Instead, we use the fact that these services must be financed out of the rebate payments that plans receive, rather than the base payments, and therefore proxy for the differential cost of different benefits offerings with the size of the rebate. We include both the core rebate amount here, as well as any rebate payments received from the Quality Bonus Payment program. Note that this approach is a partial equilibrium approach—to interpret it as the *counterfactual* amount that CMS would necessarily spend if MA plan design was restricted, we would also need to assess how bids and selection would respond, which we cannot. In the absence of these rebate payments, benefits may not fall dollar-for-dollar (Duggan et al. 2016, Cabral et al. 2018). Moreover, as we show below, selection is quite different between plans that offer more vs. less supplemental benefits, meaning the group of MA enrollees might change compositionally.

Rebates are quite large—in our main analysis, they average \$520 per beneficiary-year, roughly 11% of counterfactual FFS costs. When this component is taken out of current costs, comparing it to counterfactual FFS costs gives us a measure of the relative efficiency of public vs. private provision of standard (FFS) coverage. By this measure, MA raises the fiscal cost of identical coverage by \$186 per beneficiary-year, roughly 4% of the cost of insuring beneficiaries under FFS.

These estimates are only for 65-year-old enrollees. How might they change if we considered the full range of enrollees? While expanding to the entirety of MA cannot be done while retaining our identification strategy, we can explore the possible effects by measuring how our results change when we additionally consider 66-year-olds. We use a subsample of beneficiaries who we observe for two years before and after Medicare enrollment. We discuss this subsample further in Appendix B, and, in Appendix Table C3, replicate Table 3 for this subsample. We find smaller fiscal costs of MA in this subsample: Full MA coverage raises the cost of Medicare by only 6.7%, while the cost of standard coverage is *lower* in this sample than FFS, by 3.2%. This largely arises from the fact that we estimate, as we display in Appendix Figure B1, that spending under FFS coverage rises sharply in the second year of enrollment, while spending under MA slightly declines. This suggests that our baseline estimates may overestimate the detrimental effects of MA on federal budgets.

4.2 Favorable Selection and Imperfect Risk Adjustment

Above, we showed that one reason why MA reduces care use but raises fiscal costs arises from differences in benefits. Another is that the MA reimbursement formula fails to accurately capture the differential potential costs of beneficiaries who enroll in MA. CMS reimburses MA plans on a risk-adjusted basis. The risk adjustment is intended to compensate plans for enrolling sicker-than-average beneficiaries, so that they are not incentivized to turn those beneficiaries away as potential enrollees. However, risk adjustment is coarse

in the way it describes enrollees' health status and potential use of care. For example, MA plans are paid a fixed adjustment for enrolling a beneficiary diagnosed with diabetes. However, some diabetics may have well-controlled symptoms, leading them to use less care than the average diabetic, whereas others may have very high blood sugar, leading them to need more care than average.

Risk adjusted payments are based on the FFS population. Therefore, this imperfection poses no concerns if MA's enrollee population looks roughly like FFS's, in, e.g., the extent of diabetics with high vs. low blood sugar. However, if MA enrollment is more common among diabetics who use less care, then CMS will overestimate the cost that MA plans face to insure the average diabetic *who actually enrolls in MA*. This will inflate plan reimbursements, inflating the fiscal cost of MA. Prior work has documented the potential for this sort of favorable selection of beneficiaries into MA, focusing on the small set of beneficiaries who switch from FFS to MA, since their utilization data can be observed when they are in FFS (Newhouse et al. 2012, 2013, 2015, Brown et al. 2014). Here, we can measure this selection in a broader sample, and measure the extent to which it changes fiscal costs.

To measure favorable selection, we take the following approach. Consider two beneficiaries, one who enrolls in MA at age 65, and one who enrolls in FFS, whose enrollment would earn an MA plan the same reimbursement. If there is no favorable selection, then these two beneficiaries should cost the same to insure (i.e., have the same level of utilization) at age 64, when neither qualifies for Medicare and both are enrolled in employer-sponsored insurance. By looking in this earlier period, we can measure only differences in who selects between the two options, absent any role for different plan design in shaping costs. This approach mirrors our approach for *removing* selection bias in Section 3.

Specifically, we estimate regression models of the following linear form:

$$Y_{it} = \alpha M A_i + \kappa X_i + u_{it} \quad (2)$$

That is, we regress quarterly health care utilization at 64 under commercial coverage on a binary indicator for whether the individual will enroll in MA at 65, as well as other characteristics X_i . When there are no X variables, α captures the underlying differences in costs between future MA enrollees and future FFS enrollees at age 64. When we add additional controls, α captures the residual difference in costliness net of the contribution of characteristics represented by those controls. When X_i contains expected per-enrollee payments, α therefore represents the extent of favorable selection. We proxy for expected payments by controlling for the features that determine those payments: a beneficiary's diagnosis-based risk score (multiplied by their county benchmark) and their gender.²³

In Table 4, we report estimates of α from this exercise. First, we estimate α absent controls, reflecting differences in overall selection. *Future* MA enrollees incur \$366 (20.0%) less expenses per quarter at age 64 than *future* FFS enrollees. The goal of risk adjustment is to capture this difference. We construct our best estimate of the CMS-HCC risk score used to adjust payments by constructing it based on diagnoses observed at age 64.²⁴ If risk adjustment perfectly captures selection, our estimates should shrink to zero when we

²³The other factors determining payments—age, Medicaid status, and disability status—are uniform across all compared beneficiaries in this sample.

²⁴The employer-sponsored claims data tend to report less diagnoses per claim line than FFS Medicare data, so we may be able to observe less diagnoses than CMS is normally able to. This will not bias our estimates of selection *unless* selection is correlated

control for the risk score. Instead, we find that, net of risk adjustment, future MA enrollees spend \$167 (9.1%) less per quarter than future FFS enrollees. We also adjust for correlated variation in reimbursement rates across space and time, by controlling for cohort-by-ESHI plan type-by-year fixed effects. After doing so, our primary estimates are that eventual MA enrollees incur \$204 (11.1%) less costs per beneficiary-quarter than their like FFS counterparts. We take this as evidence that favorable selection does significantly inflate MA plan payments.

Our estimates are smaller than [Brown et al. \(2014\)](#), who estimate that MA enrollees are 16-22% less costly, and larger than [Newhouse et al. \(2015\)](#), whose estimate is 5%. These studies both study selection in the late 2000s. Our estimates are also smaller than recent white paper estimates which cover more time periods that overlap with ours, such as [Jacobson et al. \(2019\)](#) (13%) and [Lieberman et al. \(2023b\)](#) (21.5%), though not recent estimates by [MedPAC \(2024\)](#) (4-6%). All of these studies focus on those who switch from FFS to MA, not those who enroll in MA upon qualifying for Medicare.

Some researchers and policymakers have suggested that selection arises due to the fact that risk scoring only uses a limited set of inputs. Utilization is surely influenced by other factors, such as race, geography, and wealth. As Table 1 shows, these factors are more common among MA enrollees than FFS enrollees, as well. Therefore, we might expect that enriching the risk adjustment model with more predictors, particularly those that reflect socioeconomic status would reduce the scope for selection, an often-proposed policy ([Chopra et al. 2023](#), [Lieberman et al. 2023a](#)). We measure how much such a policy might reduce overpayments by showing how much adding additional observables reduces the extent of residual selection.²⁵ We sequentially add richer diagnostic categories (separate fixed effects for the HCC diagnosis indicators that are used as inputs into the risk score model), fixed effects for the beneficiary's race (white vs. non-white), and the density of their 9-digit ZIP Code (urban, suburban, large rural town, or small town/isolated rural area). We also add in various measures of social determinants of health.²⁶ The estimates from these specifications are also displayed in Table 4. α shrinks as we add additional controls, suggesting that their addition to the risk adjustment formula would reduce the extent of selection. However, although the factors we observe about beneficiaries are far richer than what CMS currently observes and is likely to be able to obtain, including all of them in risk adjustment would only reduce residual selection by 30% (\$25 per beneficiary-quarter).

4.3 Decomposing Fiscal Effects

Using our selection estimates, we decompose the role of different factors in driving the gap between the treatment effect of MA enrollment on unit costs and the final bill paid by the government. We explain it with a handful of factors. First, there is the fact that MA offers supplemental benefits, which, as before, we measure using the size of the rebate payment. Second, there is the role of selection. To estimate its effects on costs, we recompute our current cost estimates, deflating risk scores by the extent of selection. Third,

with conditions that are differently recorded between the two sets of claims data.

²⁵As [Geruso and McGuire \(2016\)](#) point out, strengthening the risk adjustment model's fit may come at the loss of weakening the incentives that insurers face to contain costs. We abstract from these concerns and simply focus on the extent to which CMS could reduce selection even when insurer and enrollee actions are held fixed.

²⁶Social determinants of health include brackets of average household income at the 9-digit ZIP Code level, brackets of the share of the 9-digit ZIP Code below the federal poverty level, and measures of the share of individuals in the 9-digit ZIP Code who are married, have received tertiary education, own their homes, own a vehicle, and speak English well.

we compute the effects of quality bonus payments (excluding their effects on rebates) and upcoding (from our calibrated value). When taking out all of these components, the final component reflects the residual gap between MA's private cost reductions and what it passes through to the government through the bidding system. This residual reflects three factors. First, plan bids may be greater than expected costs, to pay off their fixed costs or to earn markups when they face imperfect competition. Second, plans set bids uniformly across their entire enrollee population; the residual we estimate is only for 65-year-olds, but may be of different size or sign for other groups. Finally, any measurement error in estimating the other components will feed into this residual.

We benchmark the contribution of each of these factors in driving the actual fiscal costs of MA relative to the counterfactual costs of FFS enrollment, and plot this decomposition in Figure 7.²⁷ MA enrollment reduces health care use by 9%,²⁸ but raises government costs by 15.5%, a 24.5pp gap. Much recent budgetary analysis has focused on the role of imperfect risk adjustment (upcoding and favorable selection) on driving up costs (Ryan et al. 2023, MedPAC 2024). We show that these factors explain 42% (10.4pp) of the gap. Surprisingly, differences in plan benefits offerings explain a nearly-equal-sized portion (46%, 11.3pp) of the gap.

In Appendix Figure A12, we compute this decomposition for our two-year estimates. Under this calibration, all numbers are lower in level. Here, the contribution of bidding is lower—plans appear to bid below even the costs implied by their treatment effect on utilization. This likely arises from the fact that they partially pass back through the extra payments they receive due to upcoding and selection.

4.4 Heterogeneity

In Section 3, we demonstrate significant plan heterogeneity in effects of enrollment on utilization by whether the plan is an HMO or PPO plan. It is natural to also explore the relative fiscal consequences of such plans. In Figure 8, we plot the same decomposition of fiscal effects separately for HMO and PPO plans. We see that, at baseline, HMOs raise the fiscal cost of Medicare by 8.8% (\$424 per beneficiary-year), half the effect of PPOs (16.8%, \$788 per beneficiary-year). The fact that HMOs raise the cost of Medicare appears to be primarily driven by the fact that they offer significantly more generous supplemental benefits than FFS, with rebates roughly three times those received by PPOs. Once the cost of these benefits are accounted for, we estimate that HMOs *reduce* the fiscal cost of providing standard coverage. This is true even though HMOs are extraordinarily favorably selected. In fact, as we demonstrate in Appendix Figure A8, HMO enrollment explains *all of the favorable selection into MA*.²⁹ Though PPO plans do not appear to be favorably selected at all, they raise fiscal costs substantially. We estimate this largely comes from the fact that PPOs (1) raise utilization somewhat, rather than lowering it; and (2) they have larger residual components. This latter effect suggests that PPOs have higher markups than HMOs, though this only applies to 65-year-olds. This might arise even if the two types don't have strictly different overall markups if, for instance, PPOs enroll older

²⁷We plot an equivalent figure using our two-year estimates in Appendix Figure A12.

²⁸Note that the effect here is larger than our primary estimates in Section 3. This is because we focus only on medical costs, excluding prescription drugs, whose spending rises under MA. Similarly, our selection estimates in the previous section include drug costs, whereas these do not. We display these estimates in Appendix Tables C1 and C8.

²⁹This figure displays all of the plan-type-specific estimates of favorable selection that we use in this section.

populations and risk adjustment fails to fully correct for this, thus influencing plan bids ([Orsini and Tebaldi 2017](#)).

In Figure 9 we report partial decompositions for other sources of plan heterogeneity. We estimate the fiscal cost of full coverage, of standard coverage (absent rebates), and of standard coverage after adjusting risk scores to account for selection. We first investigate the HMO/PPO fiscal gap. The savings from HMO plans are offset by their large rebates. Would HMO plans that offer less supplemental benefits generate more savings? We divide plans by whether they have above- or below-median rebate payment amounts, then interact this by whether they are HMOs or PPOs. Interestingly, *even including rebate payments*, plans with higher rebates produce slightly smaller fiscal costs for CMS. After removing the rebate payments, these plans are the only plan type that reduces the fiscal cost of standard coverage. This comes despite the fact that, as shown in Appendix Figure A8, HMO plans with higher rebates are more favorably selected than those with lower rebates.³⁰ The reason for this is a sort of circularity: since plans can generally only offer generous benefits by submitting low bids, plans that do so must have achieved larger cost reductions. Appendix Table C1 confirms this: HMO plans with high rebates achieve over three times the cost reductions as HMO plans with low rebates.

While the HMO/PPO divide is striking, we find smaller differences on other margins of differentiation. Economists often think about the benefits of market provision as coming from competition. We divide state markets by the concentration of MA plans in those markets, as defined by the Herfindahl-Hirschman Index.³¹ We find that, if anything, more competitive markets are somewhat costlier to Medicare than less competitive ones. This partially comes from rebates offsetting the slightly increased cost reductions in more competitive markets, but more importantly comes from the fact that plans in more competitive markets are vastly more favorably selected, driving up their payments. We see similar results when considering urban vs. non-urban markets, which have significant overlap with more- vs. less-competitive markets.

We also generate this heterogeneity using our two-year sample, and plot the results in Appendix Figures A13 and A14. The only substantive differences between this and our one-year estimates are the sample composition (which, as we show in Appendix Table B1, is relatively unchanged) and the extent to which FFS raises spending further (relative to MA) in the second year of Medicare enrollment. Many of the qualitative comparisons remain the same but, as with our aggregate estimates, the fiscal cost of MA is much smaller in this sample, since the utilization reductions of MA enrollment are larger in the second year. Two differences are worth noting. First, when we consider HMO plans in this time window, they generate fiscal savings *even when including payments for supplemental benefits*. This suggests that the longer-run effects of managed care restrictions are large enough to even offset the cost of financing the benefits that induce enrollment in HMO plans. This is largely concentrated among plans that are able to offer more supplemental benefits (by receiving higher rebate payments), indicating their superior ability to reduce costs. Second, the two-year estimates flip our results comparing more- vs. less-competitive markets. In these estimates, plans

³⁰Note also that PPOs with high rebates are about equally as selected as HMOs with high rebates. Absent selection, both overwhelmingly lower fiscal costs. However, PPOs with above-median rebate payments are uncommon, enrolling only a quarter of all PPO enrollees.

³¹Concentration measures are generally an imperfect representation of actual competitiveness. However, [Cabral et al. \(2018\)](#) show that concentration is a strong predictor of pass-through rates of MA plan subsidy increases, which are an additional measure of market competitiveness.

in more competitive markets cost the government less and, when compared apples-to-apples against FFS, save the government a modest amount.

5 Conclusion

We have shown that MA enrollment causally reduces utilization relative to FFS enrollment. This remains true even when using panel data to adjust for potential differences in MA vs. FFS enrollment that would otherwise be unobservable, and netting out any baseline utilization differences between the two groups that already existed prior to Medicare enrollment. Correcting for this selection bias is essential given just how different the MA and FFS populations are in ways that standard observable factors fail to capture, resulting in uncorrected estimates that are three times larger relative to our corrected ones. We show that this selection also is important for policy in its own right, since, unadjusted, it results in excess payments to MA plans. As a result, we find that MA raises the fiscal cost of Medicare provision. Managed care plays an important role: MA HMO plans lower utilization substantially and, in some specifications, lower the cost of Medicare modestly, while MA PPO plans raise utilization slightly and raise fiscal costs substantially.

Our results, while simple on their face, show a complex story behind how MA “works.” The MA program allows CMS to add some managed care restraints into Medicare without having to legislatively alter the FFS program. However, since beneficiaries can select into whether they face managed care or not, they may avoid it unless the plans are attractive on another dimension, via supplemental benefits and more generous cost-sharing. However, since CMS does not *mandate* the use of utilization restrictions, these generous reimbursement arrangements incentivize the entry of PPO plans that do little to control costs. PPO plans are able to attract beneficiaries with generous benefits, financed partly off of extra payments, worsening the fiscal position of the MA program. Thinking about welfare in this setting is complicated: the government is worse off (due to fiscal losses); plans are likely better off (given profits earned from the MA program); whereas effects for beneficiaries are potentially positive by the revealed preference of their enrollment.

Our results have important lessons for policy. First, our results show that managed care in the MA program can achieve reductions in health care costs even while *increasing* the financial generosity of the product offered. While thinking about the welfare consequences of trading off cost-sharing generosity for managed care restrictions is challenging and beyond the scope of this paper, this is a key dilemma for policymakers: average out-of-pocket spending (including premiums and cost-sharing) for Medicare Parts B and D in 2024 was 26% of the average Social Security benefit, suggesting that cost-sharing is a financial constraint on beneficiary finances ([Yellen et al. 2024](#)). Shifting from price to non-price restraints on care may help improve finances for both Medicare and its beneficiaries, though at the cost of administrative burden ([Brot et al. 2023](#), [Shi 2024](#)).

Second, imperfect risk adjustment is a constraint on the ability of MA to produce benefits for the federal government. While other researchers have noted this, they have focused on selection into the MA program as an aggregate whole ([Brown et al. 2014](#), [Newhouse et al. 2015](#), [MedPAC 2024](#)). We show that not only is there across-plan heterogeneity, but that a major source of heterogeneity in selection is also a source of heterogeneity in effects on utilization. This arises quite naturally and mechanically from how MA plan de-

sign is structured. Selection appears to largely occur because residually-low-cost beneficiaries are relatively more attracted to supplemental benefits. However, to offer these benefits, plans must finance them out of rebate payments, and these rebate payments can only be achieved by reducing costs. In this way, the rebate system, which is meant to incentivize plans to invest in cost reductions below the benchmark, undoes many of the benefits it strives for. While the likely intention of the rebate system was to give lower-cost plans a way to increase their volume, it also exacerbates excess payments. Allowing plans to charge negative premiums to beneficiaries, and disentangling plan design from bids, might result in a more efficient incentive system. Indeed, differences in premiums appear to induce less favorable selection than differences in benefits offerings.

Our estimates are suggestive of the potential effects of such sweeping changes to MA plan design and reimbursement regulation. However, we have two important limitations. First, both our data and identification strategy impose sharp restrictions on which beneficiaries we can estimate effects for. Our identification strategy requires us to only estimate treatment effects for the youngest Medicare beneficiaries (who likely are lower-risk than older beneficiaries); our sample is whiter and higher-income than average new beneficiaries. Our results suggest that these characteristics are all associated with *smaller* treatment effects, suggesting that our results may be smaller than the true average (selection-corrected) treatment effect of MA on utilization. Second, we cannot fully assess the effects of regulation since we do not estimate how insurers respond to changes in MA policy ([Duggan et al. 2016](#), [Cabral et al. 2018](#), [Miller et al. 2023](#), [Vatter 2024](#), [Zahn 2025](#)). Evaluating the consequences of counterfactual payment and design reforms is an important area for further work.

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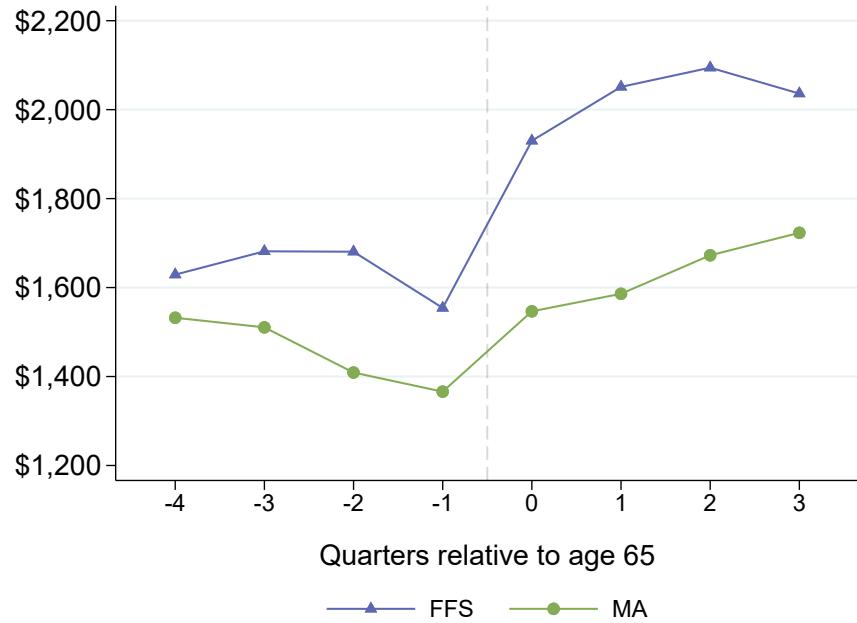
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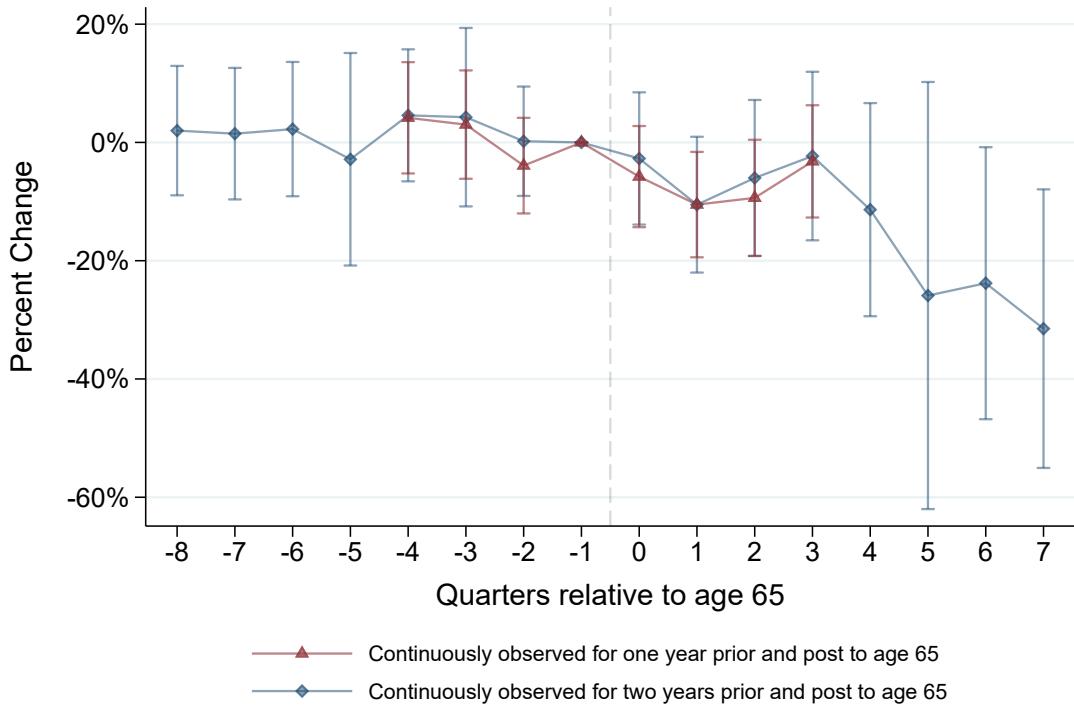
6 Figures

Figure 1: Quarterly Time Series of Average Health Care Utilization Within Matched Sample



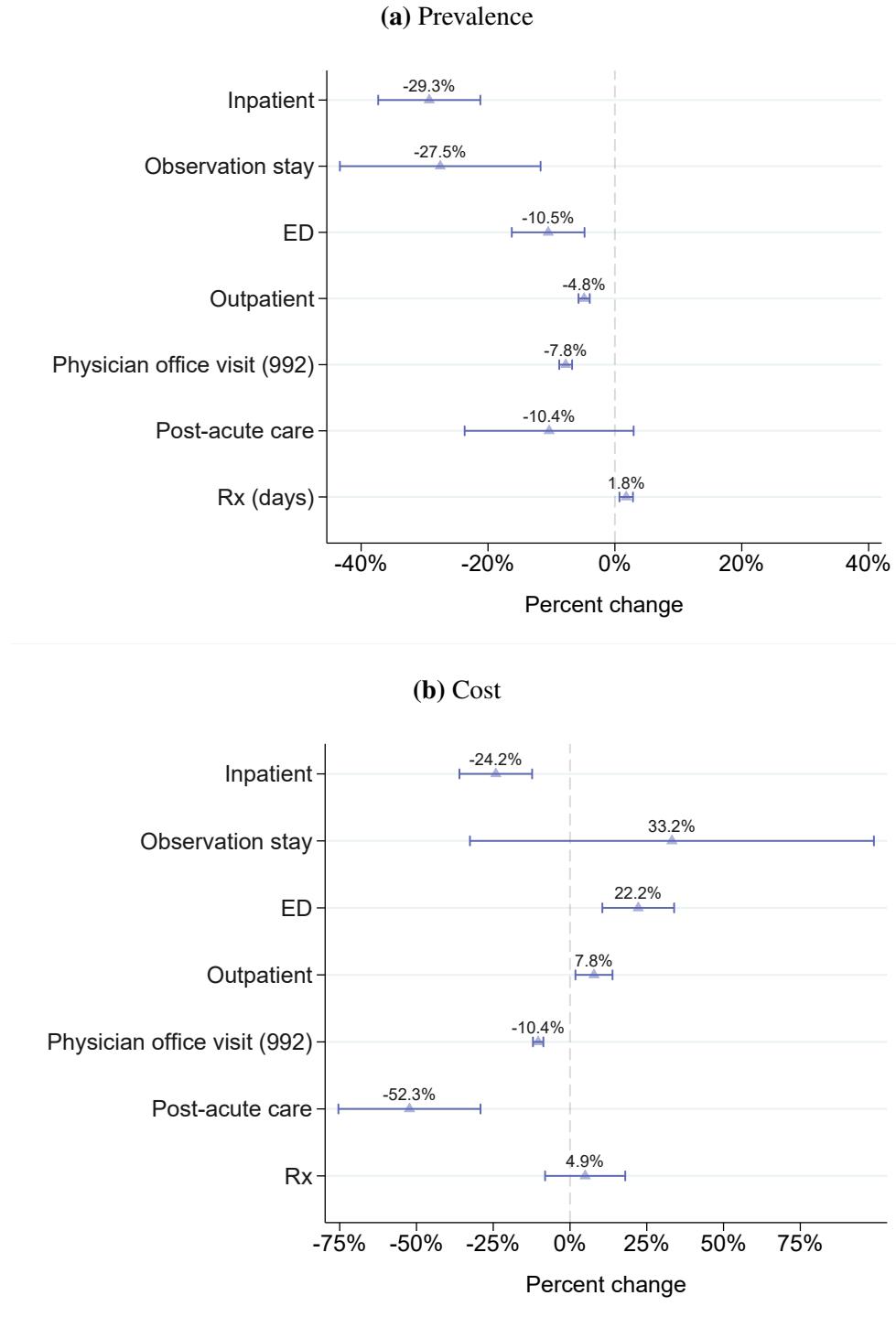
Notes: This figure presents the average quarterly health care utilization for beneficiaries in our matched sample after using the matching strategy described in Section 3.1. Our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. The two lines represent outcomes for the group of individuals who (eventually) enroll in Traditional FFS Medicare (in purple) and in Medicare Advantage (in green). For each individual, quarters are indexed relative to the quarter that the individual turned 65 and qualified to enroll in Medicare (on the horizontal axis).

Figure 2: Event Study Estimates of the Utilization Effects of Medicare Advantage



Notes: This figure presents event study estimates of the treatment effect of Medicare Advantage on overall health care utilization. Our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. For each individual, quarters are indexed relative to the quarter that the individual turned 65 and qualified to enroll in Medicare (on the horizontal axis). Regression estimates are based on the specification described in Equation (1). Estimates are rescaled in terms of estimated percent change in utilization relative to utilization in the quarter before turning 65. The red line reflects estimates from our primary analytic sample, while the blue line reflects estimates from a subsample of beneficiaries for whom we are able to observe enrollment and utilization continuously for two years before and after they turn 65 and qualify for Medicare.

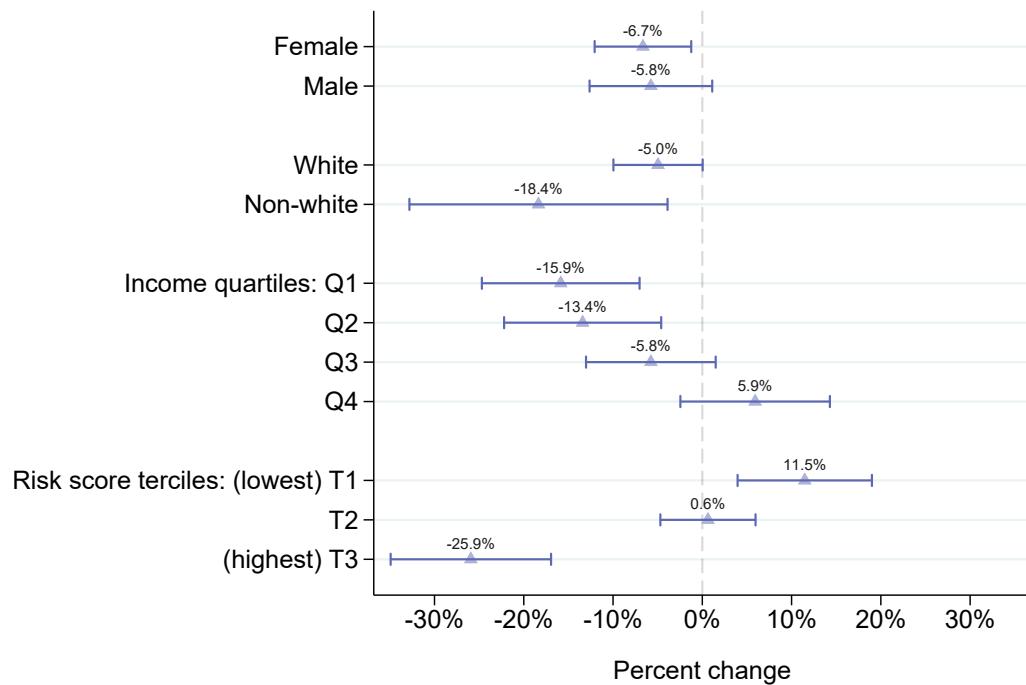
Figure 3: Heterogeneity in Utilization Effects of MA by Type of Service



Notes: These figures present estimates of the effect of MA on utilization of specific services. Each mark represents a different utilization outcome, for a given subset of health care services. The outcome in the upper panel is whether or not the beneficiary ever used the type of service in a given quarter, except the final outcome, which is the total days supply of all prescription drugs used by the beneficiary; the outcome in the lower panel is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Regression estimates are based on the specification described in Equation (1). Estimates are presented in terms of estimated percent change relative to average utilization of FFS enrollees at age 65.

Underlying estimates are given in Appendix Table A5.

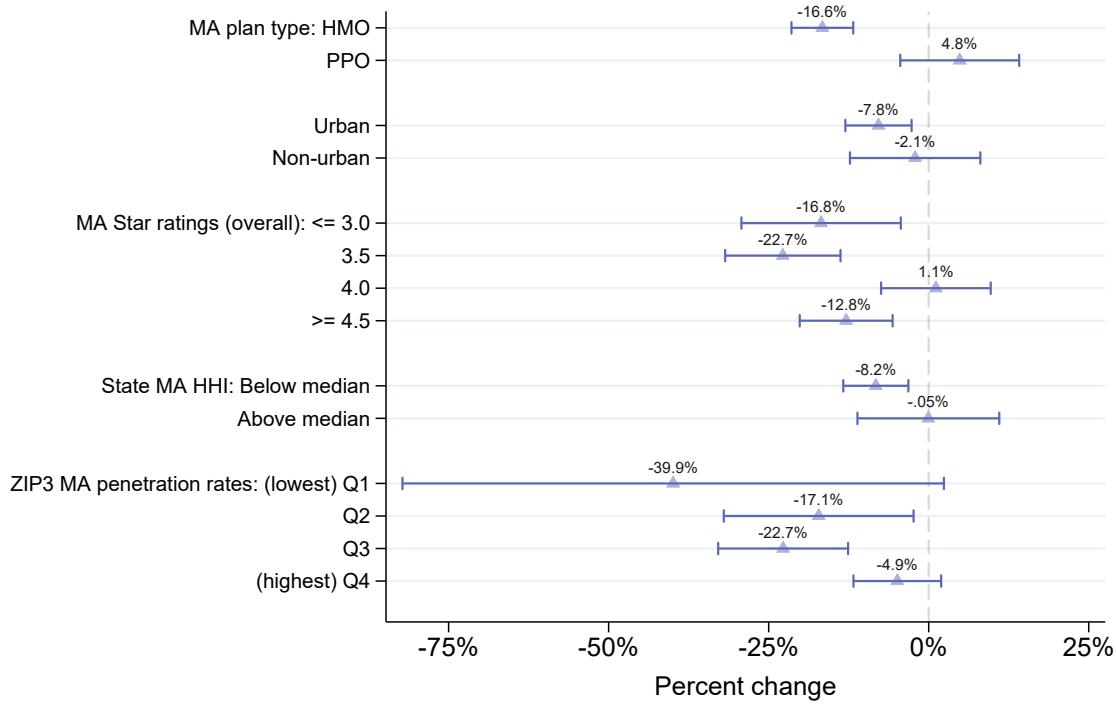
Figure 4: Heterogeneity in Utilization Effects of MA by Future MA Enrollee Characteristics



Notes: This figure presents estimates of the effect of MA on utilization for subsets of MA enrollees determined by personal characteristics. Each bar represents a treatment effect estimate for the corresponding subset of beneficiaries with the named characteristic. For all estimates, our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Regression estimates are based on the specification described in Equation (1). Estimates are presented in terms of estimated percent change relative to average utilization of FFS enrollees at age 65. Income quartiles are determined based on average income in the individual's 9-digit zip code at age 64. Risk score terciles are determined based on CMS-HCC risk scores measured at age 64.

Underlying estimates are given in Appendix Table A6.

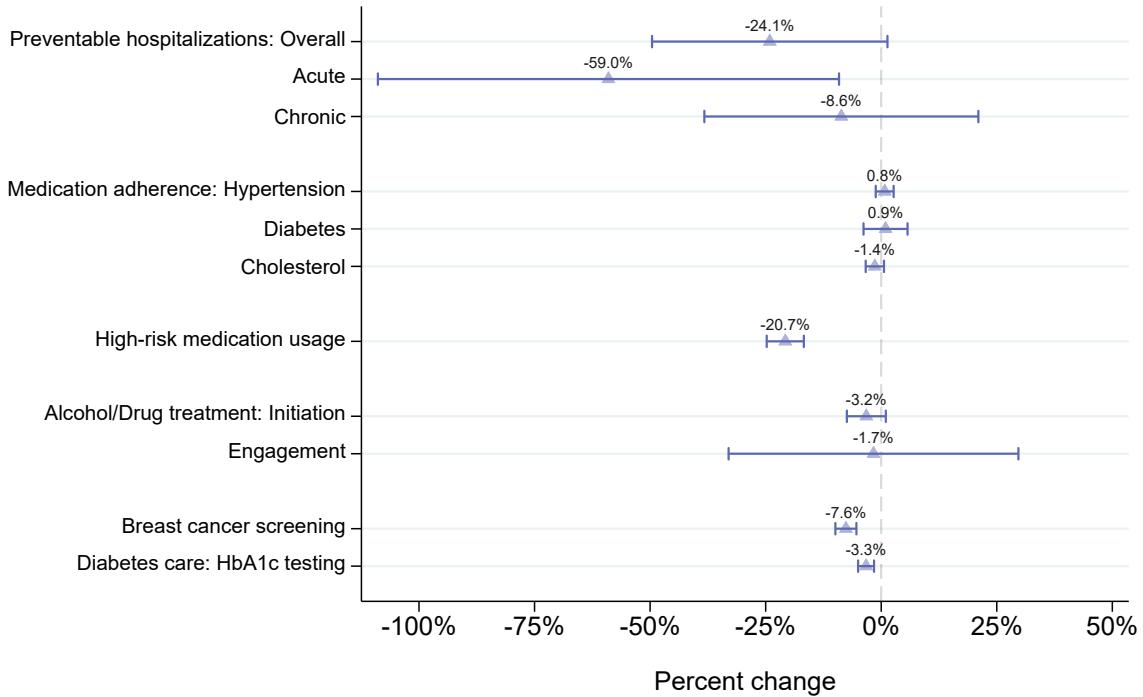
Figure 5: Estimated Effects of MA by MA Plan Characteristics



Notes: This figure presents estimates of the effect of MA on utilization for subsets of MA enrollees determined by the characteristics of their enrolled plans or geographic markets. Each bar represents a treatment effect estimate for the corresponding subset of beneficiaries in a plan or market with the named characteristic. Our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. MA penetration rates are calculated at the 3-digit ZIP Code level by dividing the number of MA enrollees by the total number of MA enrollees and FFS enrollees in our combined dataset. Regression estimates are based on the specification described in Equation (1). Estimates are presented in terms of estimated percent change relative to average utilization of FFS enrollees at age 65.

Underlying estimates are given in Appendix Table A18.

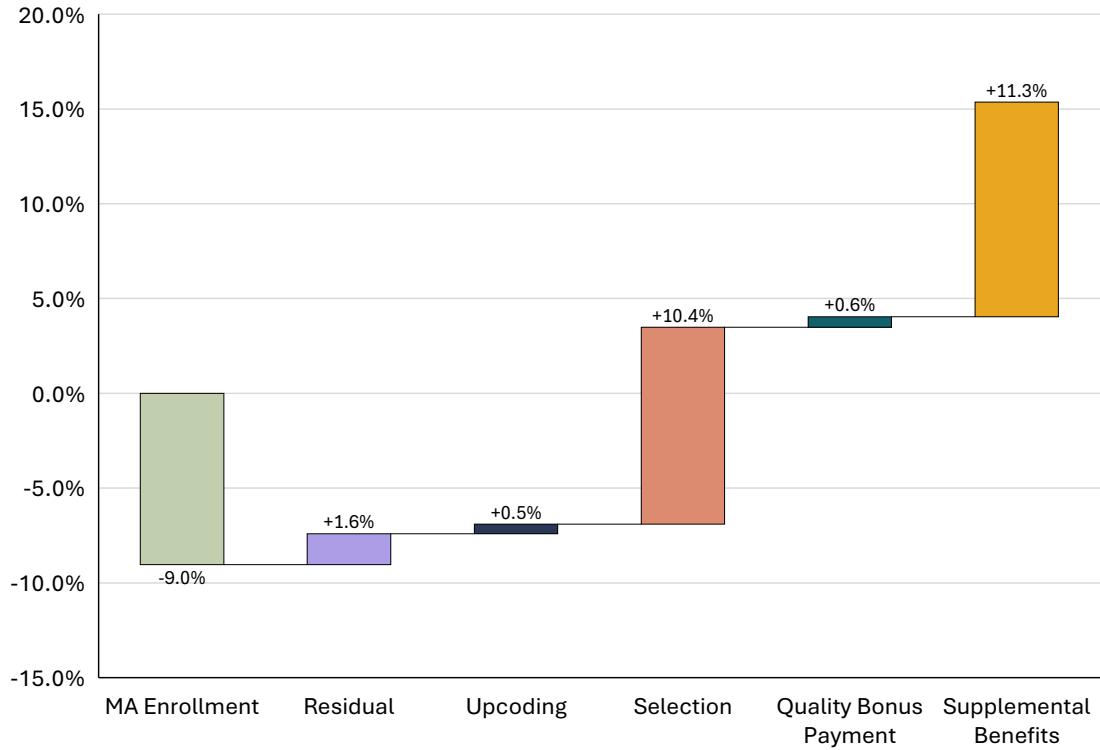
Figure 6: Estimated Effects of MA on Care Quality Measures



Notes: This figure presents estimates of the effect of MA on outcomes related to care quality. The “Hospitalizations for Preventable Complications” rows present estimates of the effect of MA on hospitalizations where the cause of the hospitalization was a preventable complication of an existing condition, as measured using definitions provided by the Agency for Healthcare Research and Quality. The “Medication Adherence” rows represent estimates of effect of MA on whether patients with a diagnosis use corresponding prescriptions identified by the Healthcare Effectiveness Data and Information Set (HEDIS) measures. The “High-risk Medication” row represents estimates of effect of MA on whether diagnosed patients use high-risk medication following HEDIS definitions. The “Alcohol/Drug Treatment” rows represent estimates of effect of MA on whether diagnosed patients initiate or engage in treatment identified by HEDIS definitions. The “Breast Cancer Screening” row presents estimates of effect of MA on whether female patients receive breast cancer screening. The “Diabetes Care” row presents estimates of effect of MA on whether diagnosed patients receive Hemoglobin A1c (HbA1c) Testing. Regression estimates are based on our preferred specification described in Equation (1), with the exception of “Alcohol/Drug Treatment” rows where we omit matching due to substantial sample loss. Estimates are presented in terms of estimated percent change relative to average outcomes among FFS enrollees at age 65.

Underlying estimates are given in Appendix Table A11.

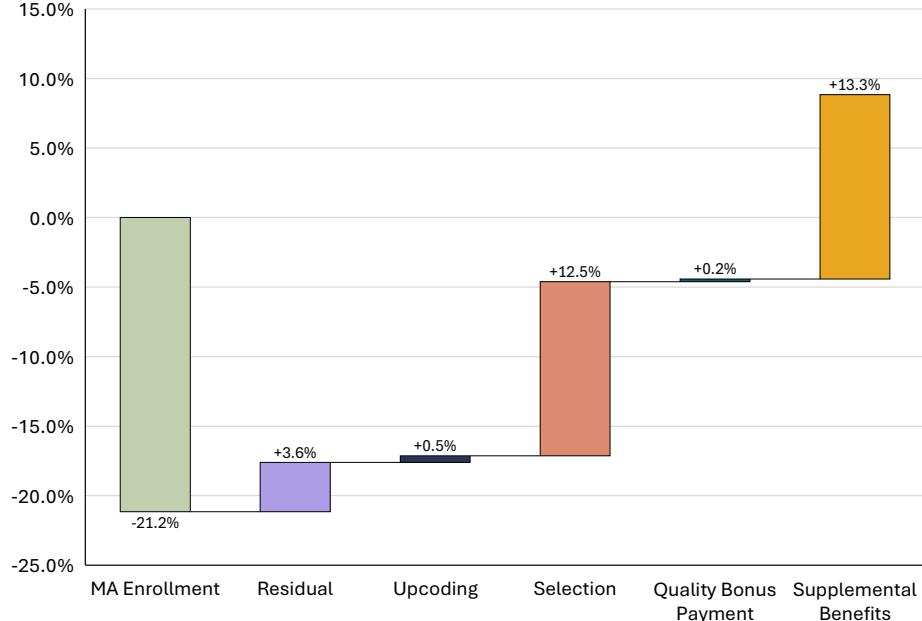
Figure 7: Fiscal Cost Decomposition



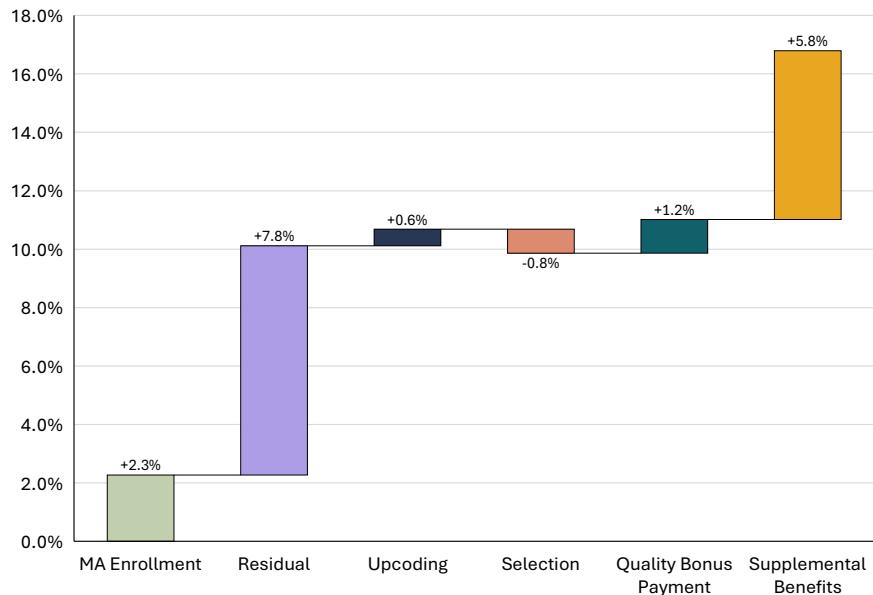
Notes: This figure presents the decomposition of fiscal costs for Parts A and B coverage as described in Section 4.3. Each bar reflects the contribution of one factor to the estimated fiscal cost of enrolling MA enrollees in MA relative to enrollment in FFS (15.4%). The “MA Enrollment” bar displays the effect of enrollment on utilization costs among enrollees. The “Upcoding” bar reflects the net upcoding factor, the difference between estimated upcoding from [Geruso and Layton \(2020\)](#) and the correction factor used by CMS. The “Selection” bar reflects the contribution of favorable selection of beneficiaries into MA. The “Quality Bonus Payment” bar reflects the contribution of quality bonus payments. The “Supplemental Benefits” bar reflects the contribution of additional payments for coverage provided by MA not otherwise provided by FFS. The “Residual” bar is the unaccounted-for amount left over after this decomposition. Each bar is presented in percent change terms, relative to our estimate of the counterfactual fiscal cost of enrollment in FFS.

Figure 8: Fiscal Cost Decomposition: HMO vs. PPO

(a) MA HMO

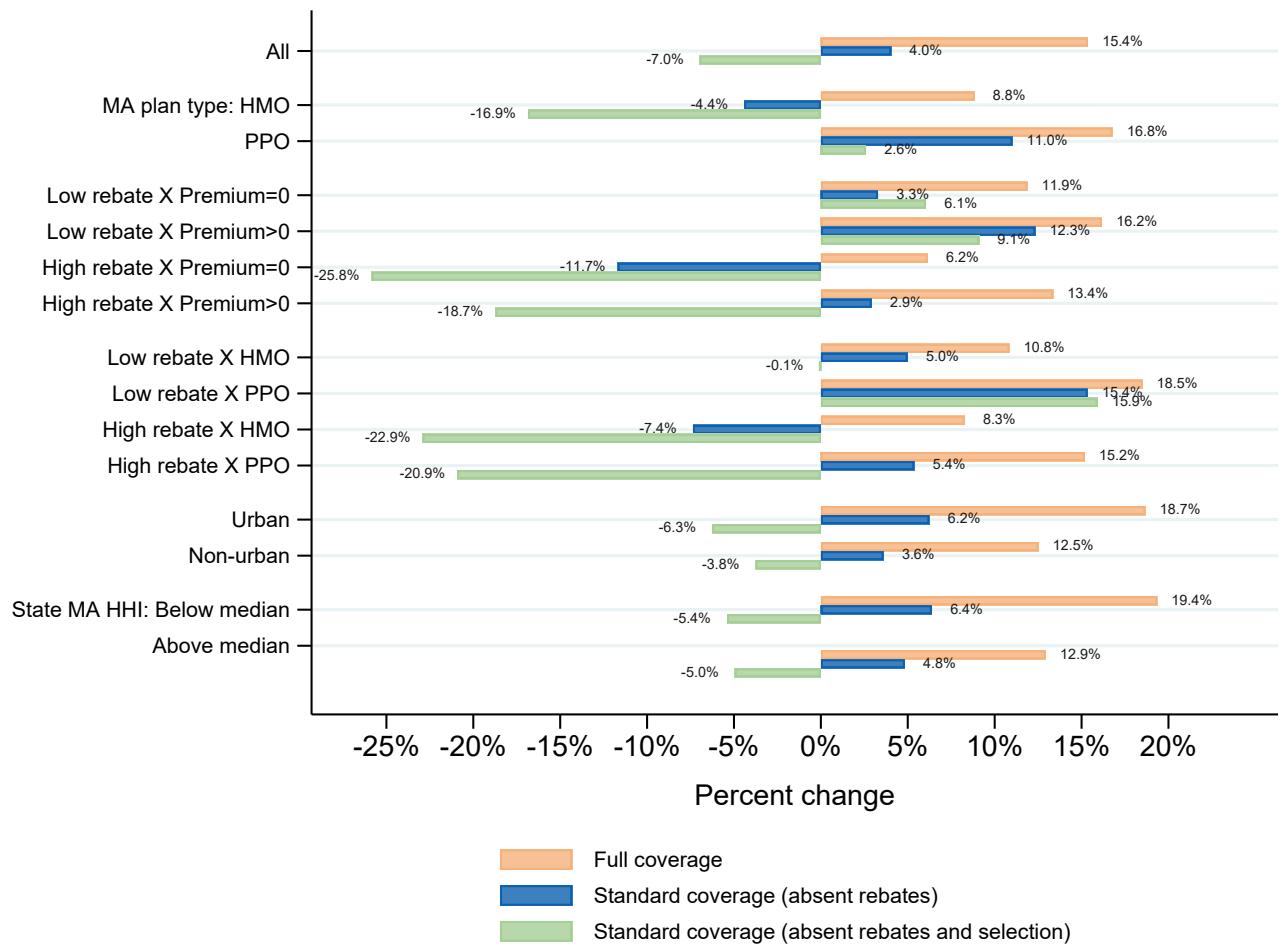


(b) MA PPO



Notes: This figure presents the decomposition of fiscal costs for Parts A and B coverage, as described in Section 4.3, separately for MA HMO and MA PPO plans. Each bar reflects the contribution of one factor to the estimated fiscal cost of enrolling MA enrollees in MA relative to enrollment in FFS (8.8% for HMO, 16.8% for PPO). The “MA Enrollment” bar displays the effect of enrollment on utilization costs among enrollees. The “Upcoding” bar reflects the net upcoding factor, the difference between estimated upcoding from [Geruso and Layton \(2020\)](#) and the correction factor used by CMS. The “Selection” bar reflects the contribution of favorable selection of beneficiaries into MA. The “Quality Bonus Payment” bar reflects the contribution of quality bonus payments. The “Supplemental Benefits” bar reflects the contribution of additional payments for coverage provided by MA not otherwise provided by FFS. The “Residual” bar is the unaccounted-for amount left over after this decomposition. Each bar is presented in percent change terms, relative to our estimate of the counterfactual fiscal cost of enrollment in FFS.

Figure 9: Changes in Fiscal Cost by Future MA Plan Characteristics



Notes: This figure presents estimates of the effect of enrolling MA enrollees in MA relative to FFS enrollment on fiscal costs to the government. We plot estimates overall (“All”) and for subsets of enrollees by characteristics of the plans they enroll in or the geographic markets they live in. Each bar represents an estimate of the percent change in fiscal costs of enrollment in those plans, relative to counterfactual costs of enrolling the same enrollees in FFS. The orange bars represent estimates of the full fiscal cost of status quo MA coverage; the blue bars represent our estimates of “standard coverage” (costs net of rebate payments for supplemental benefits), and the green bars represent our estimates of costs net of rebates *and* favorable selection.

“High rebate” is defined as plan payment rebates above median value within our sample of plans; “low rebate” is defined as plan payment rebates below median value.

Underlying estimates are given in Table 3 and Appendix Table C6.

7 Tables

Table 1: Summary Statistics

	Unmatched samples		Matched samples		Non-Inovalon
	MA	FFS	MA	FFS	MA
% Female	0.58	0.60	0.60	0.61	0.62
% White	0.91	0.96	0.90	0.91	0.84
% Urban	0.71	0.66	0.70	0.71	0.76
% HMO Prior Medicare	0.46	0.28	0.46	0.46	0.41
% PPO Prior Medicare	0.43	0.57	0.44	0.44	0.41
Zip-9 Mean Income (1000s)	\$77	\$85	\$76	\$76	\$74
Zip-9 Less than High School Education	0.35	0.32	0.36	0.35	0.37
Zip-9 Homeownership	0.84	0.85	0.84	0.83	0.81
Avg. Qtr. Spending at 64	\$1,464	\$1,830	\$1,454	\$1,636	\$1,175
Avg. Qtr. Spending at 65	\$1,634	\$2,194	\$1,632	\$2,028	–
CMS HCC-Based Risk Score at 64	0.517	0.561	0.512	0.524	0.501
Charlson Comorbidity Index (CCI) at 64	0.751	0.853	0.745	0.778	0.737
# Individuals	25,470	180,087	22,784	113,463	53,849

Notes: This table presents summary statistics for three cohorts of enrollees whom we continuously observe one year before and after age 65: enrollees who enrolled in Medicare Advantage plans captured by Inovalon (the first and third columns), enrollees who enrolled in Fee-For-Service at age 65 (the second and fourth columns), enrollees who were enrolled in employer-sponsored plans captured by Inovalon, but then enrolled in Medicare Advantage plans that are not captured by Inovalon (the last column). We match each enrollee in the primary sample MA cohort with up to five enrollees in the FFS cohort as described in Section 3.1, and the restricted matched sample is plotted in the third and fourth columns. Our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels.

Table 2: Effects of Medicare Advantage Enrollment on Total Health Care Utilization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Effect of MA enrollment	-650.3 (34.1)	-422.9 (32.3)	-358.3 (40.0)	-182.8 (39.7)	-196.6 (44.8)	-149.3 (40.4)	-124.9 (49.1)
Post-65 FFS baseline	\$2,194	\$2,194	\$2,028	\$2,194	\$2,194	\$2,194	\$2,028
Percent change	-29.6%	-19.3%	-17.7%	-8.3%	-9.0%	-6.8%	-6.2%
Risk adjusted?		✓	✓	✓			
Using pre-65 data?				✓	✓	✓	✓
Individual FEs?					✓	✓	✓
Plan Characteristics FEs?						✓	✓
Matching?			✓				✓
# Individuals	182,821	182,821	136,247	182,821	205,557	205,557	136,247

Notes: This table presents estimates of the effects of MA enrollment on total health care utilization. For all estimates, our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Column 7 presents our preferred specification, described in Equation (1). Changes in percentage points are rescaled estimates in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the average quarterly total health care utilization at age 65 of the control FFS cohort. Sample sizes in columns 1, 2, and 4 are smaller since they control for some characteristics that are not available for all in-sample beneficiaries.

Table 3: Accounting Ledger

Current Costs		Counterfactual Costs	
Item	Cost	Item	Cost
Base Payment	+\$4,734	Average MA Costs Per 65 Year Old	+\$4,738
Rebate	+\$360	Average MA Treatment Effect	+\$582
Quality Bonus Payment		Cost-Sharing [†]	-\$798
Rebate Multiplier	+\$69		
Rebate Benchmark Adjustment	+\$92	Administrative Costs	+\$74
Base Payment Benchmark Adjustment	+\$26		
Net Upcoding Factor	+\$26		
Total (excl. rebates)	\$4,783	Total	\$4,597
Total	\$5,303		

Notes: This table presents an accounting breakdown of the current costs of offering Medicare Advantage as an option to enrolling beneficiaries (in the left panel) and the cost of counterfactually moving all MA enrollees into FFS (in the right panel). This panel analyzes these costs for 65-year old enrollees, and all statistics are measured at the person-year level. “Base Payment” is the average base risk-adjusted capitated reimbursement rate paid to plans for enrollees in our sample. “Rebate” is the average rebate paid by the federal government to plans on enrollees’ behalf. “Quality Bonus Payment” reflects additional payments based on the quality bonus payment system: increases to rebate-sharing rates (“Rebate Multiplier”) and increases to county benchmarks that both increase rebates (“Rebate Benchmark Adjustment”) and base payments (“Base Payment Benchmark Adjustment”). “Net Upcoding Factor” reflects upcoding, calibrated as the difference between the extent of upcoding estimated by [Geruso and Layton \(2020\)](#) and the upcoding penalty adjustment used by CMS. “Average MA Costs” is our measure of utilization averaged over our sample. “Average Treatment Effect” is our estimate of the impact of moving enrollees from MA to FFS on yearly total allowed utilization. “Cost-Sharing” is the amount of utilization paid by enrollees (or their supplemental insurance plans). “Administrative Costs” is a calibrated measure, assuming that administrative costs are 1.4 cents per dollar of utilization [Kaiser Family Foundation \(2019\)](#). [†] Note that this is a negative cost since it is paid by beneficiaries rather than by CMS.

Table 4: Favorable Selection of MA Enrollees

	(1)	(2)	(3)	(4)	(5)	(6)
MA_i	-366.4 (42.1)	-167.2 (39.4)	-204.0 (38.5)	-190.8 (38.3)	-164.7 (42.8)	-142.1 (44.6)
Pre-65 FFS baseline	\$1,830	\$1,830	\$1,830	\$1,830	\$1,830	\$1,830
Percent change	-20.0%	-9.1%	-11.1%	-10.4%	-9.0%	-7.8%
Risk scores?	✓	✓	✓	✓	✓	✓
Gender?	✓	✓	✓	✓	✓	✓
Cohort-market FEs?		✓	✓	✓	✓	✓
Richer diagnosis FEs?			✓	✓	✓	✓
Race/Urban?				✓	✓	✓
SDOH?					✓	
# Individuals	205,557	205,557	205,557	205,557	182,821	180,975

Notes: This table presents estimates of the favorable selection of future MA enrollees. Each estimate reflects the extent to which future MA enrollees use more or less care than future FFS enrollees at age 64 after controlling for factors indicated in the lower panel. Our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Column (3) presents estimates based on our preferred specification, Equation (2), controlling for risk score and fixed effects for state of residence, month of birth, urban status of county of residence, and type of plan enrolled in at 64 (HMO/PPO). Changes in percentage points are rescaled estimates by control means based on the average utilization at age 64 of the FFS cohort.

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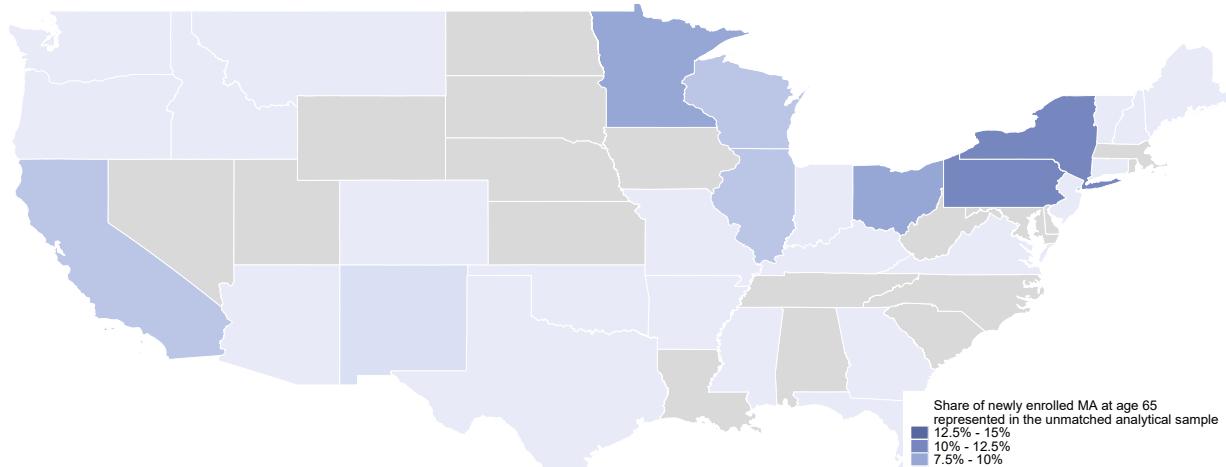
Appendix for:

**Privatizing Social Insurance:
Medicare Advantage vs. Traditional Medicare**

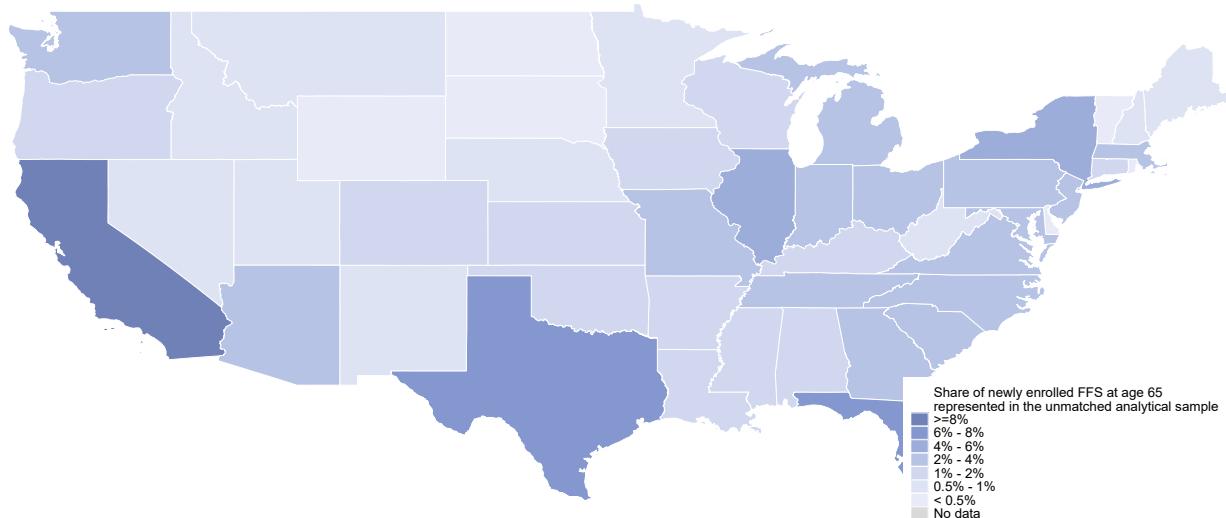
A Supplemental Figures and Tables

A.1 Supplemental Figures

Appendix Figure A1: Geographical Representation of MA and FFS Enrollees

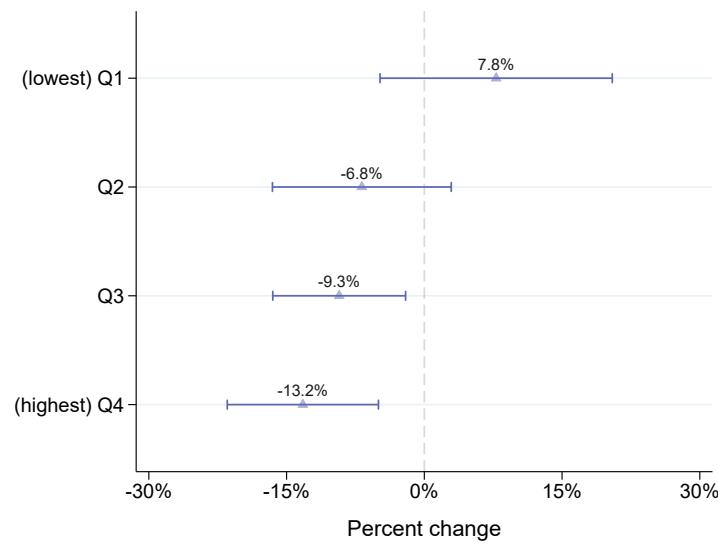


(a) MA



(b) FFS

Notes: This figure presents the geographical representation of MA and FFS enrollees in our (unmatched) analytic sample. Each state is colored according to the share of enrollees within the sample who are recorded as residing in that state at age 65.

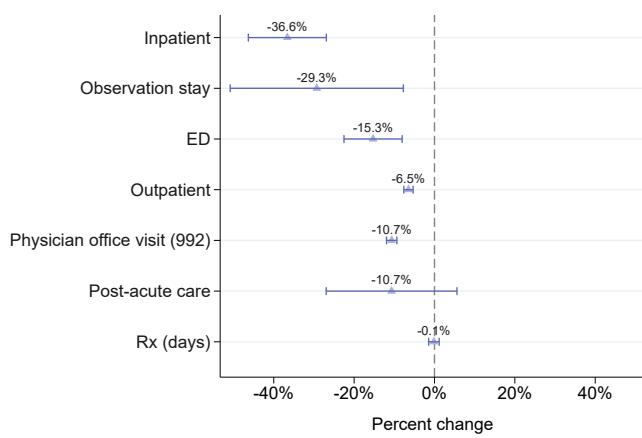
Appendix Figure A2: Estimated Effects of MA by Estimated Propensity of MA Enrollment

Notes: This figure presents estimates of the effect of MA on utilization by estimated propensity to enroll in MA according to characteristics measured when they are age 64. The first quartile (Q1) represents the group least likely to enroll in MA, whereas the fourth quartile (Q4) represents those most likely to enroll in MA. Our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Regression estimates are based on the specification described in Equation (1). Estimates are presented in terms of estimated percent change relative to average utilization of FFS enrollees at age 65.

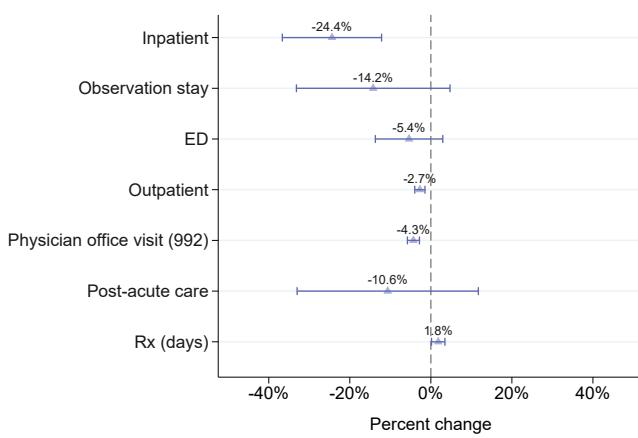
Underlying estimates are given in Appendix Table A10.

Appendix Figure A3: Utilization Effects of MA by Future MA Plan Type: HMO vs. PPO

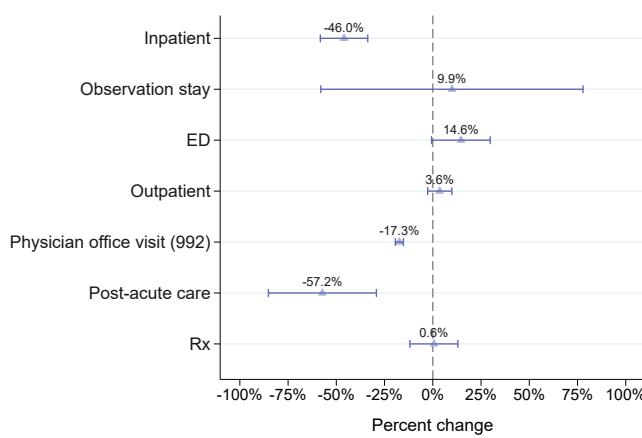
(a) Prevalence: HMO



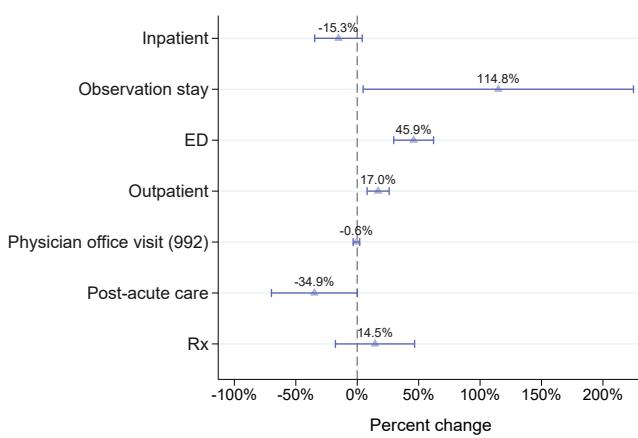
(b) Prevalence: PPO



(c) Cost: HMO



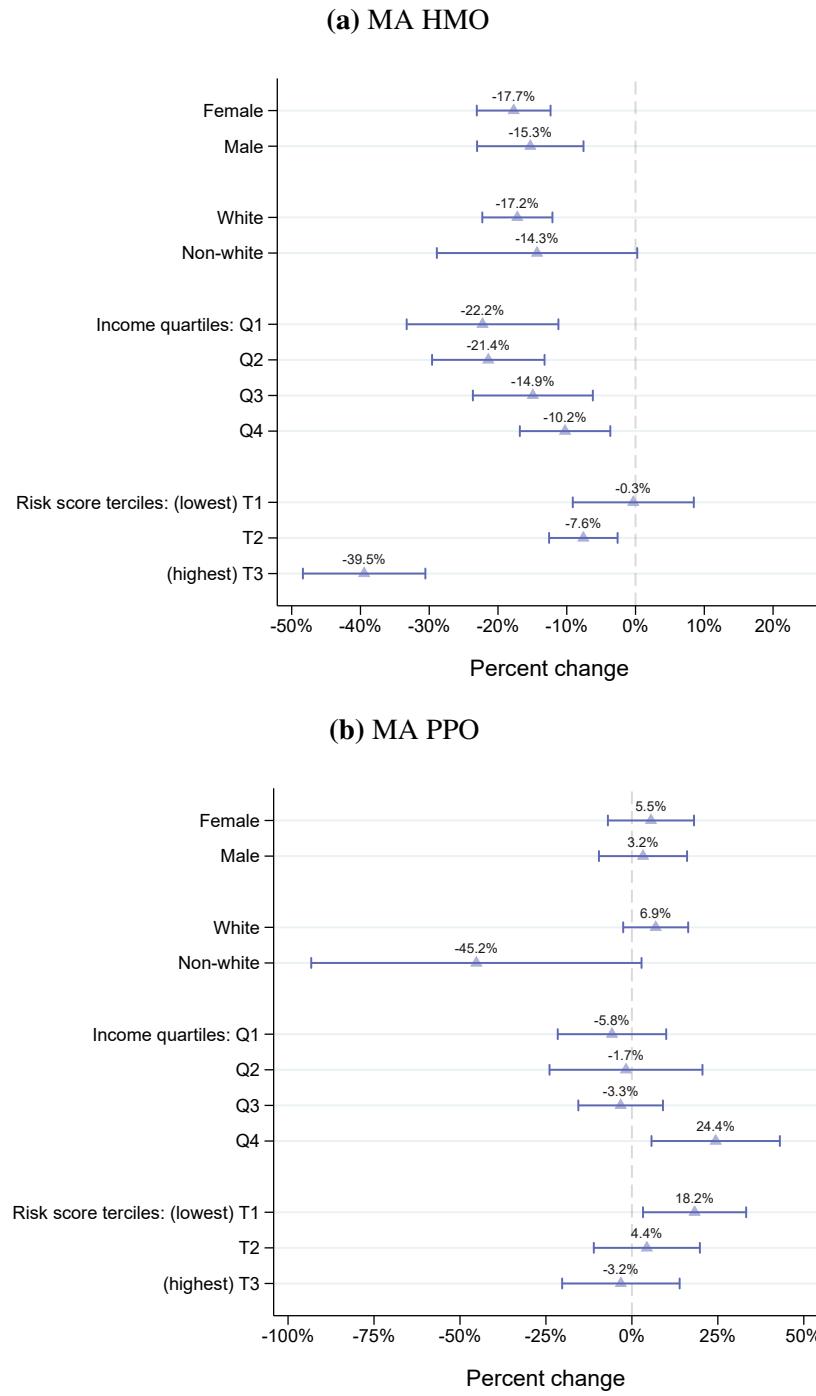
(d) Cost: PPO



Notes: These figures present estimates of the effect of MA on utilization of specific services by future MA plan type. Each mark represents a different utilization outcome, for a given subset of health care services. The outcome in the upper panel is whether or not the beneficiary ever used the type of service in a given quarter, except the final outcome, which is the total days supply of all prescription drugs used by the beneficiary; the outcome in the lower panel is utilization, measured as quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Regression estimates are based on the specification described in Equation (1). Estimates are presented in terms of estimated percent change relative to average utilization of FFS enrollees at age 65.

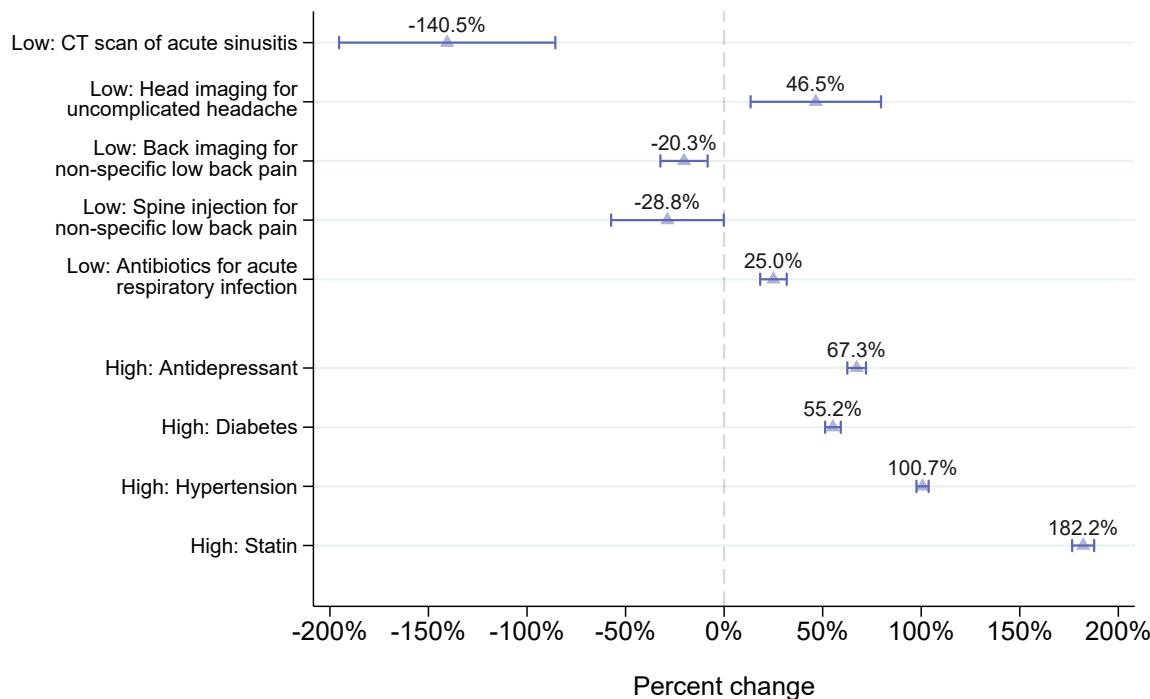
Underlying estimates are given in Appendix Table A7.

Appendix Figure A4: Heterogeneity in Utilization Effects of MA by Enrollee Characteristics and MA Plan Type



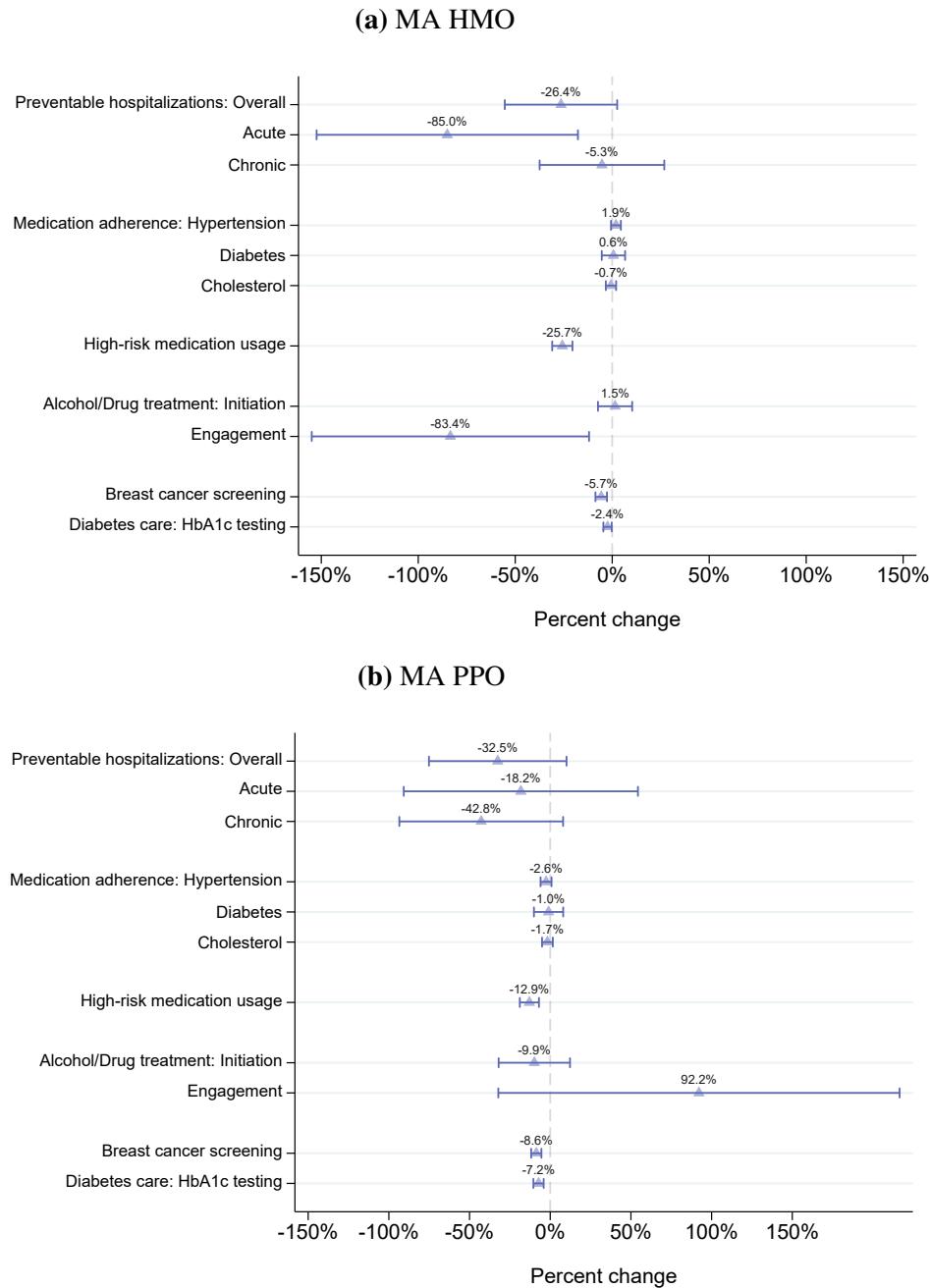
Notes: These figures present estimates of the effect of MA on utilization by MA enrollee characteristics and the type of plan enrolled in by the MA enrollee. Each bar represents a utilization outcome based on the corresponding enrollee characteristics. For all estimates, our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Regression estimates are based on the specification described in Equation (1). Estimates are presented in terms of estimated percent change relative to average utilization of FFS enrollees at age 65. Income quartiles are determined based on average income in the individual's 9-digit zip code at age 64. Risk score terciles are determined based on CMS-HCC risk scores measured at age 64.

Underlying estimates are given in Appendix Tables A8 and A9.

Appendix Figure A5: Estimated Effects of MA on Low- and High-Value Care

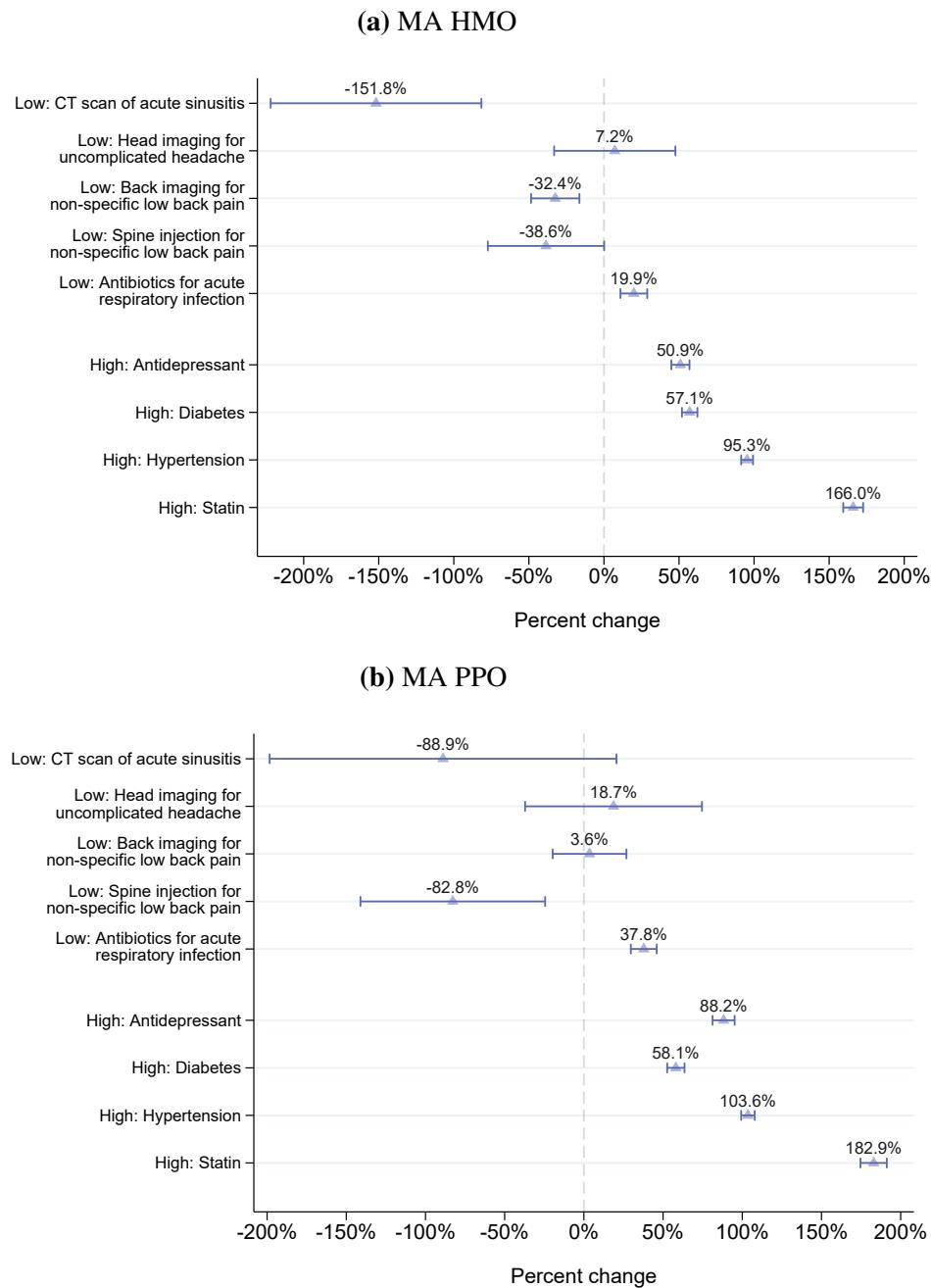
Notes: This figure presents estimates of the effect of MA on outcomes related to low- and high-value care used in the prior literature (Schwartz et al. 2014, Brot-Goldberg et al. 2017, Curto et al. 2019). Regression estimates are based on the specification described in Equation (1). Estimates are presented in terms of estimated percent change relative to average outcomes of FFS enrollees at age 65.

Underlying estimates are given in Appendix Table A14.

Appendix Figure A6: Estimated Effects of MA on Care Quality Measures: HMO vs. PPO

Notes: This figure presents estimates of the effect of MA on outcomes related to care quality separately for those who enroll in MA HMO plans and MA PPO plans. The “Hospitalizations for Preventable Complications” rows present estimates of the effect of MA on hospitalizations where the cause of the hospitalization was a preventable complication of an existing condition, as measured using definitions provided by the Agency for Healthcare Research and Quality. The “Medication Adherence” rows represent estimates of effect of MA on whether patients with a diagnosis use corresponding prescriptions identified by the Healthcare Effectiveness Data and Information Set (HEDIS) measures. The “High-risk Medication” row represents estimates of effect of MA on whether diagnosed patients use high-risk medication following HEDIS definitions. The “Alcohol/Drug Treatment” rows represent estimates of effect of MA on whether diagnosed patients initiate or engage in treatment identified by HEDIS definitions. The “Breast Cancer Screening” row presents estimates of effect of MA on whether female patients receive breast cancer screening. The “Diabetes Care” row presents estimates of effect of MA on whether diagnosed patients receive Hemoglobin A1c (HbA1c) Testing. Regression estimates are based on our preferred specification described in Equation (1), with the exception of “Alcohol/Drug Treatment” rows where we omit matching due to substantial sample loss. Estimates are presented in terms of estimated percent change relative to average outcomes of FFS enrollees at age 65.

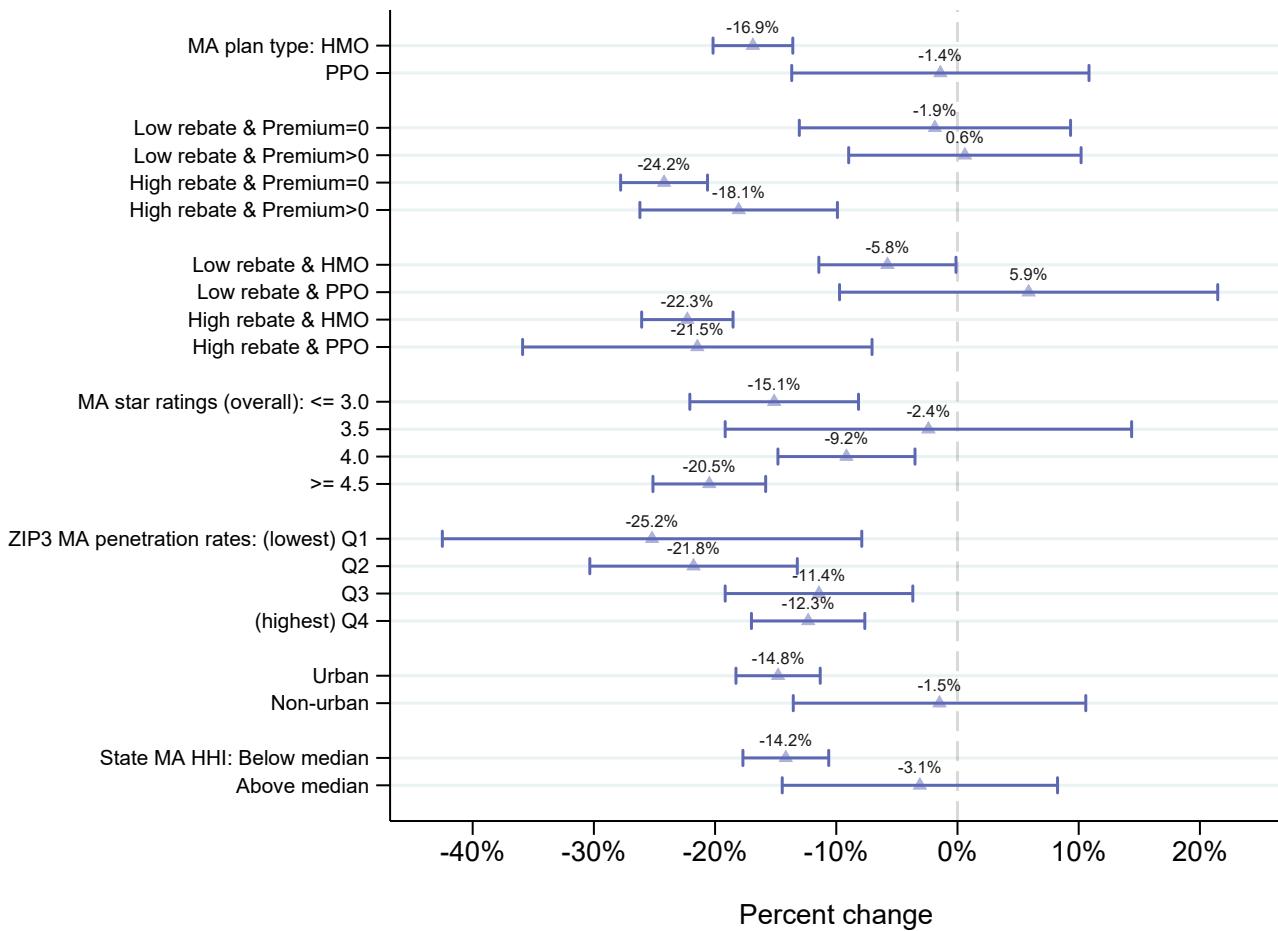
Underlying estimates are given in Appendix Tables A12 and A13.

Appendix Figure A7: Estimated Effects of MA on Low- and High-Value Care: HMO vs. PPO

Notes: This figure presents estimates of the effect of MA on outcomes related to low- and high-value care used in the prior literature (Schwartz et al. 2014, Brot-Goldberg et al. 2017, Curto et al. 2019) separately for those who enroll in MA HMO plans and MA PPO plans. Regression estimates are based on the specification described in Equation (1). Estimates are presented in terms of estimated percent change relative to average outcomes of FFS enrollees at age 65.

Underlying estimates are given in Appendix Tables A15 and A16.

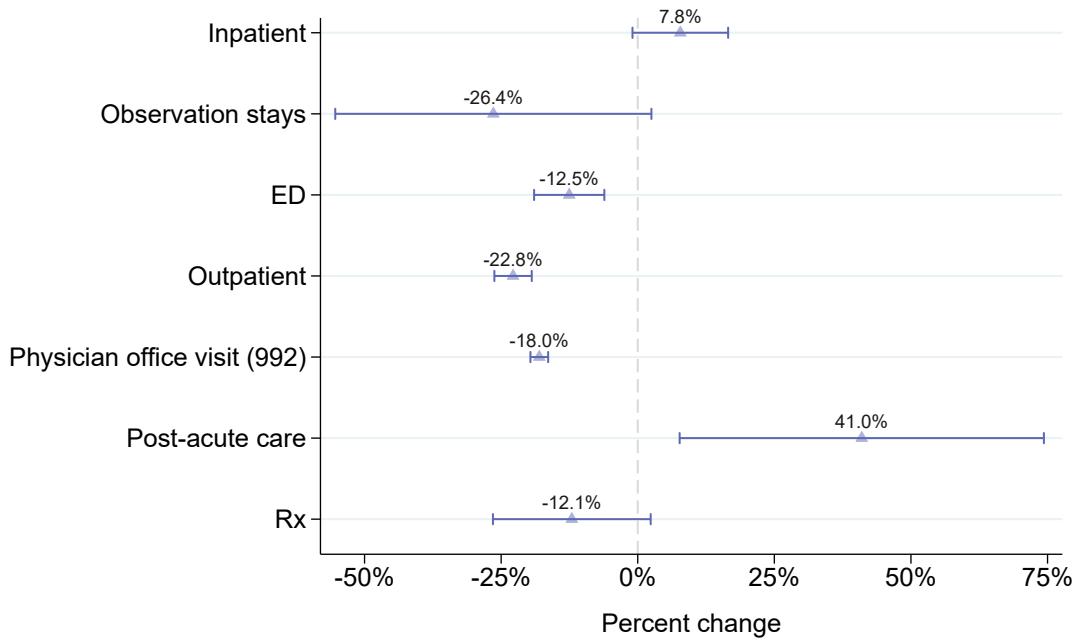
Appendix Figure A8: Heterogeneity in Favorable Selection of Future MA Enrollees by MA Plan Characteristics



Notes: This figure presents estimates of the favorable selection of beneficiaries into MA plans according to the characteristics of those plans. Each bar represents an estimate based on the corresponding MA plan characteristic. MA penetration rates are calculated at the 3-digit ZIP Code level by dividing the number of MA enrollees (Inovalon) by the total number of MA enrollees (Inovalon) and FFS enrollees. For all estimates, our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Regression estimates are based on the specification described in Equation (2) controlling for risk scores at age 64, cohort-market fixed effects. Estimates are presented in terms of estimated percent change relative to average utilization of future FFS enrollees at age 64.

Underlying estimates are given in Appendix Table A22.

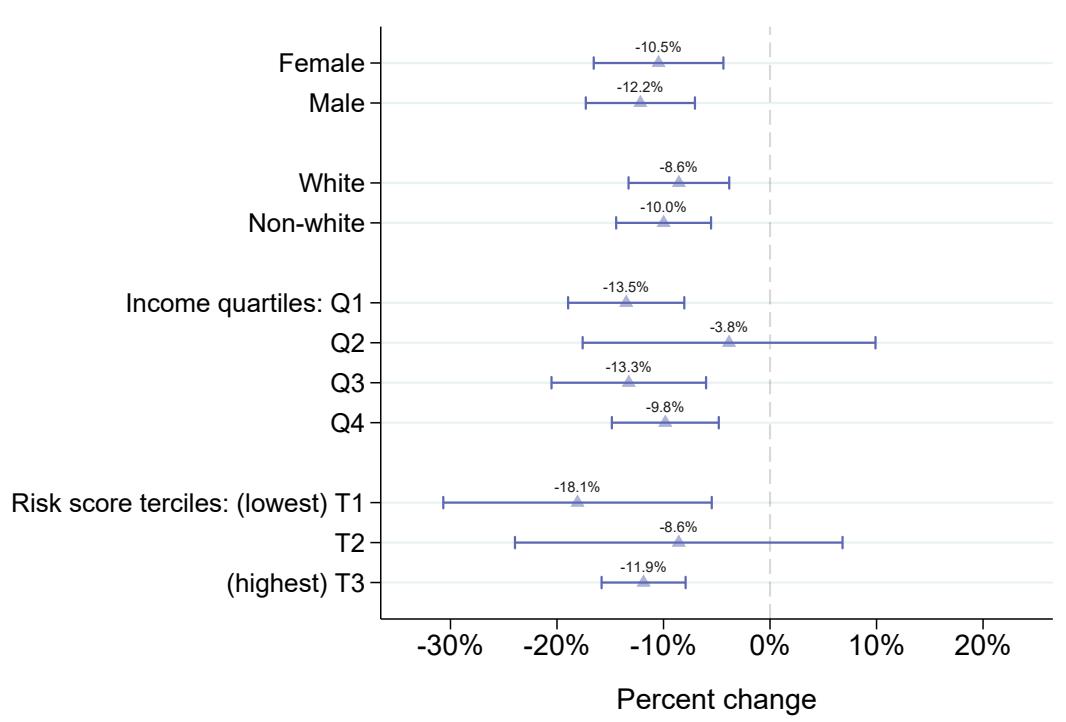
Appendix Figure A9: Heterogeneity in Favorable Selection of Future MA Enrollees by Type of Service



Notes: This figure presents estimates of differences in utilization between future MA enrollees and future FFS at age 64 for specific types of services (favorable selection). Each bar represents a selection estimate for a given subset of health care services. For all estimates, the outcome is quarterly total allowed spending, with prices normalized to FFS reimbursement rates. Regression estimates are based on specification Equation (2), controlling for risk scores at age 64, gender, and cohort-market fixed effects. Estimates are presented in terms of estimated percent differences relative to average quarterly spending at age 64 by the FFS cohort.

Underlying estimates are given in Appendix Table A19.

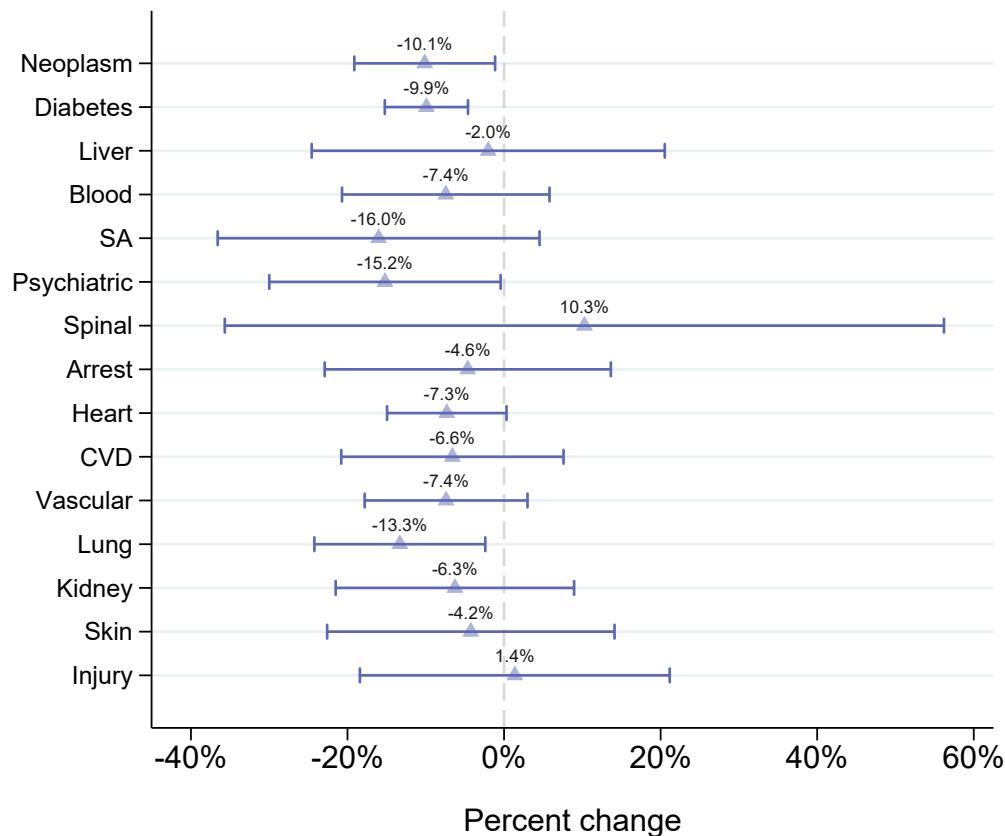
Appendix Figure A10: Heterogeneity in Favorable Selection of Future MA Enrollees by Enrollee Characteristics



Notes: This figure presents estimates of the favorable selection of future MA enrollees characteristics by gender, race, ZIP-9 average income quartiles, and risk score terciles. Each bar represents an estimate based on the corresponding future MA enrollee characteristics. Income quartiles are determined based on average income in the individual's 9-digit zip code at age 64. Risk score terciles are determined based on CMS-HCC risk scores measured at age 64. For all estimates, our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Regression estimates are based on the specification described in Equation (2) controlling for risk scores at age 64, cohort-market fixed effects. Estimates are presented in terms of estimated percent differences relative to average quarterly spending at age 64 by the FFS cohort.

Underlying estimates are given in Appendix Table A20.

Appendix Figure A11: Heterogeneity in Favorable Selection of Future MA Enrollees by HCC High-Level Groupings



Notes: This figure presents estimates of the favorable selection of future MA enrollees by common Hierarchical Condition Category (HCC) high-level groupings. Each bar represents an estimate based on the corresponding HCC. “SA” stands for Substance Abuse, and “CVD” stands for cerebrovascular disease. For all estimates, our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Regression estimates are based on the specification described in Equation (2) controlling for risk scores at age 64, cohort-market fixed effects. Estimates are presented in terms of estimated percent differences relative to average quarterly spending at age 64 by the FFS cohort.

Underlying estimates are given in Appendix Table A21.

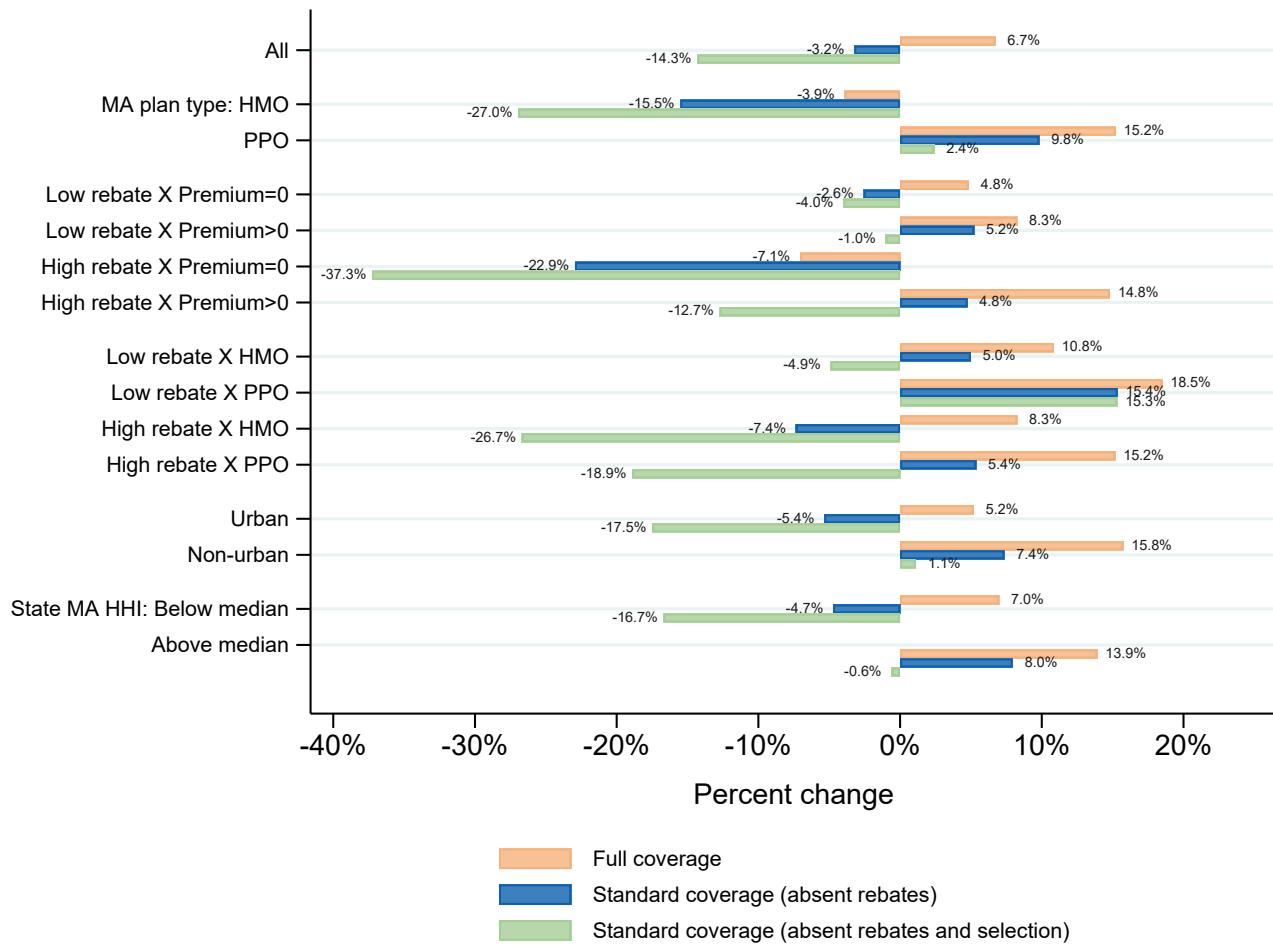
Appendix Figure A12: Fiscal Cost Decomposition (Two-year Estimates)

Notes: This figure presents the decomposition of fiscal costs for Parts A and B coverage, as described in Section 4.3, for the subsample of beneficiaries for who we can observe enrolled continuously for two years before and after they turn 65 and qualify for Medicare. Each bar reflects the contribution of one factor to the estimated fiscal cost (at ages 65 and 66) of enrolling MA enrollees in MA relative to enrollment in FFS (6.7%). The “MA Enrollment” bar displays the effect of enrollment on utilization costs among enrollees. The “Upcoding” bar reflects the net upcoding factor, the difference between estimated upcoding from Geruso and Layton (2020) and the correction factor used by CMS. The “Selection” bar reflects the contribution of favorable selection of beneficiaries into MA. The “Quality Bonus Payment” bar reflects the contribution of quality bonus payments. The “Supplemental Benefits” bar reflects the contribution of additional payments for coverage provided by MA not otherwise provided by FFS. The “Residual” bar is the unaccounted-for amount left over after this decomposition. Each bar is presented in percent change terms, relative to our estimate of the counterfactual fiscal cost of enrollment in FFS.

Appendix Figure A13: Fiscal Cost Decomposition: HMO vs. PPO (Two-year Estimates)

Notes: This figure presents the decomposition of fiscal costs for Parts A and B coverage, as described in Section 4.3, for the subsample of beneficiaries for who we can observe enrolled continuously for two years before and after they turn 65 and qualify for Medicare, separately for MA HMO and MA PPO plans. Each bar reflects the contribution of one factor to the estimated fiscal cost (at ages 65 and 66) of enrolling MA enrollees in MA relative to enrollment in FFS (-3.9% for HMO, 15.2% for PPO). The “MA Enrollment” bar displays the effect of enrollment on utilization costs among enrollees. The “Upcoding” bar reflects the net upcoding factor, the difference between estimated upcoding from [Geruso and Layton \(2020\)](#) and the correction factor used by CMS. The “Selection” bar reflects the contribution of favorable selection of beneficiaries into MA. The “Quality Bonus Payment” bar reflects the contribution of quality bonus payments. The “Supplemental Benefits” bar reflects the contribution of additional payments for coverage provided by MA not otherwise provided by FFS. The “Residual” bar is the unaccounted-for amount left over after this decomposition. Each bar is presented in percent change terms, relative to our estimate of the counterfactual fiscal cost of enrollment in FFS.

Appendix Figure A14: Changes in Fiscal Cost by Future MA Plan Characteristics (Two-year Estimates)



Notes: This figure presents estimates of the effect of enrolling MA enrollees in MA relative to FFS enrollment on fiscal costs to the government, for the subsample of beneficiaries for who we can observe enrolled continuously for two years before and after they turn 65 and qualify for Medicare. We measure yearly fiscal costs at ages 65 and 66. We plot estimates overall (“All”) and for subsets of enrollees by characteristics of the plans they enroll in or the geographic markets they live in. Each bar represents an estimate of the percent change in fiscal costs of enrollment in those plans, relative to counterfactual costs of enrolling the same enrollees in FFS. The orange bars represent estimates of the full fiscal cost of status quo MA coverage; the blue bars represent our estimates of “standard coverage” (costs net of rebate payments for supplemental benefits), and the green bars represent our estimates of costs net of rebates *and* favorable selection.

“High rebate” is defined as plan payment rebates above median value within our sample of plans; “low rebate” is defined as plan payment rebates below median value.

Underlying estimates are given in Appendix Tables C3 and C7.

A.2 Supplemental Tables

Appendix Table A1: Inclusion and Exclusion Criteria for Main Analytical Sample

Step	Inclusion/Exclusion Criteria for Cohort Identification	Medicare FFS		Medicare Advantage (Inovalon)		Medicare Advantage (Non-Inovalon)	
		N remaining	% reduced	N remaining	% reduced	N remaining	% reduced
1	Enrolled in MA (Part C & D) or FFS (A, B, & D) between 2012–2019, within 1 year of turning 65, with commercial coverage in Inovalon data the month prior to Medicare enrollment	727,309	100.0%	218,956	100.0%	351,553	100.0%
2	Limit to index years 2015–2018; require continuous commercial enrollment and Inovalon plan tracking (medical + Rx) during 12 months before Medicare enrollment	246,115	33.8%	64,702	29.6%	101,962	29.0%
3	Require continuous MA/FFS enrollment through 12 months post-Medicare; exclude dual eligibles; for Inovalon MA, require post-Medicare plan tracking through month 12	232,075	94.3%	60,030	92.8%	90,312	88.6%
4	Exclude those with more than 1 month of commercial enrollment during 12 months post-Medicare	180,670	77.8%	36,726	61.2%	68,128	75.4%
5	Require pre-Medicare commercial plan to be tracked in Inovalon for at least 1 month after Medicare enrollment	180,129	99.7%	36,671	99.9%	67,827	99.6%
6	Exclude members ever enrolled in Employer Group Waiver Plan (EGWP) during 12 months post-Medicare enrollment	180,129	100.0%	25,474	69.5%	53,863	79.4%
7	Newly enrolled in MA (Part C&D) OR FFS (A, B, & D) within 3 months of turning 65	180,087	99.98%	25,470	99.98%	53,849	99.97%

Notes: This table presents the number and percentage of enrollees who remained in the main analytical sample after applying each inclusion and exclusion criterion. Our initial sample is the one described in the first row. The “N remaining column” represents how many unique individuals are left after all the restrictions up to and including the row. The “% reduced” columns present the share of individuals are removed due to the noted restriction relative to the sample before that restriction (but including all others before it). The three groups described are those who enroll in FFS when they turn 65; those who enroll in an Inovalon-covered MA plan; and those who enroll in an Inovalon-uncovered MA plan

Appendix Table A2: Summary Statistics: Comparison to Broader Sample

	Unmatched samples		Broad sample	
	MA	FFS	MA	FFS
% Female	0.58	0.60	0.56	0.51
% White	0.91	0.96	0.74	0.79
Local Mean Income (1000s)	\$77	\$85	\$59	\$62
Local Less than High School Education	0.35	0.32	0.30	0.30
Local Homeownership	0.84	0.85	0.72	0.73
Avg. Qtr. Spending at 65	\$1,634	\$2,194	-	\$1,984
# Individuals	25,470	180,087	2,189,249	6,383,409

Notes: This table presents summary statistics for our primary analytic sample (in the first two columns) and for a sample of 65-year-old beneficiaries appearing in the MBSF between 2015-2017 enrolled in either MA or FFS for at least 3 months in the focal year. For our analytic sample, “Local” measures are at the 9-digit zip code level. For the broad sample, “Local” measures are at the county level. Our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels.

Appendix Table A3: Poisson Regression: Effects of MA Enrollment on Total Health Care Utilization

	(1)	(2)	(3)	(4)
Effect of MA enrollment	-26.2%	-23.0%	-9.6%	-6.3%
	(1.9)	(2.4)	(3.2)	(4.1)
Risk adjusted?	✓	✓	✓	✓
Using pre-65 data?			✓	✓
Matching?		✓		✓
Comparison to linear models				
Percent change	-19.3%	-17.7%	-8.3%	-7.5%

Notes: This table presents estimates of the effects of MA enrollment on total health care utilization. For all estimates, our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. These table reflects estimates using Poisson regression, after which the primary estimates are transformed by the transformation $\exp(\beta) - 1$ to reflect estimated percent changes due to MA enrollment. The “Comparison to linear models” row presents estimates from an OLS regression using the same sample, where percent changes are computed by comparing the estimated treatment effect in levels to average utilization among FFS enrollees at age 65.

Appendix Table A4: Alternative Matching Procedure without Replacement of Control Units

	Matching w/ replacement	Matching w/o replacement
Effect of MA enrollment	-124.9 (49.1)	-155.7 (47.2)
Post-65 FFS baseline	\$2,028	\$2,086
Percent change	-6.2%	-7.5%

Notes: This table presents estimates of the effects of MA enrollment on total health care utilization. For all estimates, our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. The first column reflects our primary estimates using matching, as also shown in Table 2. The second column reflects the same estimating approach *except* that, when matching is done, matches are chosen without replacement such that control FFS enrollees can only be sampled a maximum of once.

Appendix Table A5: Heterogeneity in Utilization Effects of MA by Type of Service

	Inpatient	Observation stay	ED	Outpatient	Physician office	Post-acute care	Rx
Prevalence	-0.00671 (0.00094)	-0.00233 (0.00068)	-0.00517 (0.00144)	-0.0358 (0.00333)	-0.0514 (0.00342)	-0.000962 (0.00063)	4.35 (1.32)
Post-65 FFS baseline	0.0229	0.00850	0.0492	0.738	0.663	0.00928	244.0
Percent change	-29.2%	-27.5%	-10.5%	-4.8%	-7.8%	-10.4%	1.8%
Cost	-100.0 (25.0)	3.27 (3.30)	10.4 (2.80)	54.19 (21.4)	-18.71 (1.56)	-36.0 (8.14)	20.6 (27.8)
Post-65 FFS baseline	\$415	\$9.88	\$47.0	\$695	\$181	\$68.9	\$418
Percent change	-24.2%	33.1%	22.2%	7.8%	-10.3%	-52.3%	4.9%
# Individuals	136,247	136,247	136,247	136,247	136,247	136,247	136,247

Notes: This table presents estimates of the effect of MA on utilization of specific services. For all estimates in the “Prevalence” section (upper panel), the outcome is whether or not the beneficiary ever used the type of service in a given quarter, except the final outcome, which is the total days supply of all prescription drugs used by the beneficiary. For all estimates in the “Cost” section (lower panel), the outcome is quarterly total allowed spending, with prices normalized to FFS reimbursement rates. Regression estimates are based on the specification described in Equation (1). Estimates are rescaled in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the quarterly average prevalence or total health care spending at age 65 of the matched FFS cohort.

Appendix Table A6: Heterogeneity in Utilization Effects of MA by Enrollee Characteristics

	Female	Male	White	Non-white
Effect of MA enrollment	-137.0 (57.2)	-114.1 (69.8)	-101.3 (52.3)	-348.6 (140.8)
Post-65 FFS baseline	\$2,060	\$1,981	\$2,042	\$1,899
Percent change	-6.7%	-5.8%	-5.0%	-18.4%
# Individuals	81,052	55,195	123,112	13,135

	Income Quartiles			
	Q1	Q2	Q3	Q4
Effect of MA enrollment	-283.8 (81.0)	-254.5 (85.7)	-119.3 (77.1)	139.7 (101.4)
Post-65 FFS baseline	\$1,789	\$1,898	\$2,071	\$2,362
Percent change	-15.9%	-13.4%	-5.8%	5.9%
# Individuals	34,066	35,137	33,233	33,811

	RAF Quartiles		
	T1	T2	T3
Effect of MA enrollment	214.7 (72.2)	12.3 (53.3)	-582.9 (103.6)
Post-65 FFS baseline	\$1,871	\$1,951	\$2,248
Percent change	11.5%	0.6%	-25.9%
# Individuals	32,934	59,130	44,183

Notes: This table presents estimates of the effect of MA on utilization by enrollee characteristics. For all estimates, our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Regression estimates are based on the specification described in Equation (1). Estimates are rescaled in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the total health care quarterly average spending at age 65 of the matched FFS cohort. Income quartiles are determined based on average income in the individual's 9-digit zip code at age 64. Risk score terciles are determined based on CMS-HCC risk scores measured at age 64.

Appendix Table A7: Heterogeneity in Type of Services Utilization Effects of MA: MA Plan Type HMO vs. PPO

	Inpatient	Observation stay	ED	Outpatient	Physician office	Post-acute care	Rx
Prevalence: MA HMO	-0.00826 (0.00112)	-0.00241 (0.00091)	-0.00761 (0.00184)	-0.04802 (0.00436)	-0.07195 (0.00443)	-0.00106 (0.00082)	-0.34196 (1.61920)
Post-65 FFS baseline	0.0226	0.0082	0.0498	0.7417	0.6755	0.0099	243.0000
Percent change	-36.6%	-29.3%	-15.3%	-6.5%	-10.7%	-10.7%	-0.1%
Cost: MA HMO	-187.3 25.6	1.02 3.56	6.72 3.58	23.9 21.2	-32.2 2.0	-39.1 9.8	2.40 26.4
Post-65 FFS baseline	\$407	\$10.3	\$46.1	\$663	\$186	\$68.3	\$417
Percent change	-46.0%	9.9%	14.6%	3.6%	-17.3%	-57.2%	0.6%
# Individuals	84,127	84,127	84,127	84,127	84,127	84,127	84,127
Prevalence: MA PPO	-0.00597 (0.00153)	-0.00132 (0.00090)	-0.00266 (0.00210)	-0.02011 (0.00477)	-0.02838 (0.00501)	-0.00098 (0.00105)	4.64073 (2.14593)
Post-65 FFS baseline	0.0244	0.0093	0.0495	0.7431	0.6604	0.0092	255.0000
Percent change	-24.4%	-14.2%	-5.4%	-2.7%	-4.3%	-10.6%	1.8%
Cost: MA PPO	-66.6 43.1	11.12 5.44	21.26 3.82	125.5 33.7	-1.1 2.4	-23.1 11.8	64.33 73.1
Post-65 FFS baseline	\$437	\$9.7	\$46.3	\$738	\$176	\$66.2	\$444
Percent change	-15.3%	114.8%	45.9%	17.0%	-0.6%	-34.9%	14.5%
# Individuals	39,400	39,400	39,400	39,400	39,400	39,400	39,400

Notes: This table presents estimates of the effect of MA on type of services utilization by MA HMO vs. PPO plans. For all estimates in the “Prevalence” sections, the outcome is whether or not the beneficiary ever used the type of service in a given quarter, except the final outcome, which is the total days supply of all prescription drugs used by the beneficiary. For all estimates in the “Cost” sections, the outcome is quarterly total allowed spending, with prices normalized to FFS reimbursement rates. Regression estimates are based on the specification described in Equation (1). Estimates are rescaled in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the quarterly average prevalence or total health care spending at age 65 of the matched FFS cohort

Appendix Table A8: Heterogeneity in Utilization Effects of MA HMO by Enrollee Characteristics

	Female	Male	White	Non-white
Effect of MA enrollment	-360.8 (56.0)	-296.1 (76.8)	-346.4 (52.7)	-267.8 (139.7)
Post-65 FFS baseline	\$2,036	\$1,935	\$2,016	\$1,870
Percent change	-17.7%	-15.3%	-17.2%	-14.3%
# Individuals	50,851	33,276	72,741	11,386
Income Quartiles	Q1	Q2	Q3	Q4
Effect of MA enrollment	-395.6 (100.6)	-405.4 (79.4)	-308.8 (92.5)	-229.8 (75.7)
Post-65 FFS baseline	\$1,778	\$1,894	\$2,068	\$2,243
Percent change	-22.2%	-21.4%	-14.9%	-10.2%
# Individuals	21,018	20,986	21,065	21,058
RAF Quartiles	T1	T2	T3	
Effect of MA enrollment	-6.0 (83.6)	-148.4 (50.0)	-850.9 (98.5)	
Post-65 FFS baseline	\$1,853	\$1,955	\$2,156	
Percent change	-0.3%	-7.6%	-39.5%	
# Individuals	19,964	36,897	27,266	

Notes: This table presents estimates of the effect of MA HMO on utilization by enrollee characteristics. For all estimates, our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Regression estimates are based on the specification described in Equation (1). Estimates are rescaled in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the total health care quarterly average spending at age 65 of the matched FFS cohort. Income quartiles are determined based on average income in the individual's 9-digit zip code at age 64. Risk score terciles are determined based on CMS-HCC risk scores measured at age 64.

Appendix Table A9: Heterogeneity in Utilization Effects of MA PPO by Enrollee Characteristics

	Female	Male	White	Non-white
Effect of MA enrollment	136.3 (117.7)	136.7 (67.2)	102.1 (145.8)	509.9 -(936.2)
Post-65 FFS baseline	\$2,122	\$2,079	\$2,106	\$2,070
Percent change	6.4%	6.6%	4.8%	24.6%
# Individuals	23,235	16,165	37,819	1,581
Income Quartiles	Q1	Q2	Q3	Q4
Effect of MA enrollment	152.6 -(109.3)	208.4 -(31.3)	135.7 -(70.3)	244.6 (622.5)
Post-65 FFS baseline	\$1,887	\$1,826	\$2,150	\$2,555
Percent change	8.1%	11.4%	6.3%	9.6%
# Individuals	9,841	9,847	9,872	9,840
RAF Quartiles	T1	T2	T3	
Effect of MA enrollment	149.2 (354.0)	157.3 (86.5)	207.3 -(75.6)	
Post-65 FFS baseline	\$1,941	\$1,988	\$2,366	
Percent change	7.7%	7.9%	8.8%	
# Individuals	9,828	16,201	13,371	

Notes: This table presents estimates of the effect of MA PPO on utilization by enrollee characteristics. For all estimates, our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Regression estimates are based on the specification described in Equation (1). Estimates are rescaled in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the total health care quarterly average spending at age 65 of the matched FFS cohort. Income quartiles are determined based on average income in the individual's 9-digit zip code at age 64. Risk score terciles are determined based on CMS-HCC risk scores measured at age 64.

Appendix Table A10: Estimated Effects of MA by Baseline Propensity of Future MA Enrollment

	Propensity Scores			
	(lowest) Q1	Q2	Q3	(highest) Q4
Effect of MA enrollment	144.3 (119.6)	-137.9 (101.2)	-192.7 (77.1)	-286.0 (91.3)
Post-65 FFS baseline	\$1,844	\$2,027	\$2,079	\$2,162
Percent change	7.8%	-6.8%	-9.3%	-13.2%
# Individuals	34,086	34,124	34,049	33,988

Notes: This table presents estimates of the effect of MA on utilization by enrollee characteristics. For all estimates, our measure of utilization is quarterly total allowed spending after prices of claims have been normalized to average FFS reimbursement rate levels. Regression estimates are based on the specification described in Equation (1). Estimates are rescaled in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the total health care quarterly average spending at age 65 of the matched FFS cohort. Income quartiles are determined based on average income in the individual's 9-digit zip code at age 64. Risk score terciles are determined based on CMS-HCC risk scores measured at age 64.

Appendix Table A11: Regression Analysis: Effects of MA on Quality Measures

	Preventable Complications		
	Overall	Acute	Chronic
Effect of MA enrollment	-1.40 (0.76)	-1.01 (0.44)	-0.36 (0.64)
Post-65 FFS baseline per 1,000 beneficiaries	5.82	1.72	4.21
Percent change	-24.1%	-59.0%	-8.6%
# Individuals	134,299	134,299	134,299

	Medication Adherence			Treatment Appropriateness		
	Hypertension	Diabetes	Cholesterol	High-risk Medication Usage	Alcohol and Other Drug Initiation	Engagement
Effect of MA enrollment	6.52 (8.51)	8.00 (20.9)	-11.44 (8.44)	-47.4 (4.7)	-27.3 (18.3)	-1.7 (16.4)
Post-65 FFS baseline per 1,000 beneficiaries	856	854	832	228	847	102
Percent change	0.8%	0.9%	-1.4%	-20.7%	-3.2%	-1.7%
# Individuals	45,288	16,230	52,959	134,299	3,258	3,258

	Preventive Screenings		Diabetes Care
	Breast Cancer Screening	Hemoglobin A1c (HbA1c) Testing	
Effect of MA enrollment	-39.2 (6.00)		-30.9 (8.36)
Post-65 FFS baseline per 1,000 beneficiaries	514		945
Percent change	-7.6%		-3.3%
# Individuals	82,154		21,904

Notes: The top panel of this table presents estimates of the effect of MA on hospitalizations where the cause of the hospitalization was a preventable complication of an existing condition, as measured using definitions provided by the Agency for Healthcare Research and Quality. The middle panel of this table presents estimates of the effect of MA on outcomes related to medication adherence and treatment appropriateness. Outcomes are constructed based on the standard Healthcare Effectiveness Data and Information Set (HEDIS) measures. The “Medication Adherence” columns represent estimates of effect of MA on whether patients with a diagnosis use corresponding prescriptions. The “High-risk Medication” column represents estimates of effect of MA on whether patients use high-risk medication. The “Alcohol/Drug Treatment” columns represent estimates of effect of MA on whether patients initiate or engage in treatment. The lower panel of this table presents estimates of the effect of MA on outcomes related to breast cancer screening and diabetes care, identified by HEDIS measures. The “Breast Cancer Screening” column presents estimates of effect of MA on whether female patients receive breast cancer screening. The “Diabetes Care” column presents estimates of effect of MA on whether patients receive Hemoglobin A1c (HbA1c) Testing. Regression estimates are based on our preferred specification described in Equation (1), with the exception of “Alcohol/Drug Treatment” outcomes where we use the same specification as in Table 2 Column (5) without matching due to substantial sample loss. Changes in percentage points are rescaled estimates in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the utilization at age 65 of the matched FFS cohort.

Appendix Table A12: Regression Analysis: Effects of MA on Quality Measures: MA HMO

	Preventable Complications		
	Overall	Acute	Chronic
Effect of MA enrollment	-1.54 (0.86)	-1.20 (0.49)	-0.24 (0.74)
Post-65 FFS baseline per 1,000 beneficiaries	5.82	1.41	4.48
Percent change	-26.4%	-85.0%	-5.30%
# Individuals	80,991	80,991	80,991

	Medication Adherence			Treatment Appropriateness		
	Hypertension	Diabetes	Cholesterol	High-risk Medication Usage	Alcohol and Other Drug Initiation	Engagement
Effect of MA enrollment	16.3 (11.1)	5.30 (26.2)	-5.36 (11.2)	-59.5 (6.18)	12.3 (38.1)	-86.4 (38.0)
Post-65 FFS baseline per 1,000 beneficiaries	850	850	822	231	841	104
Percent change	1.9%	0.6%	-0.7%	-25.7%	1.5%	-83.4%
# Individuals	27,424	10,203	31,524	79,383	660	660

	Preventive Screenings		Diabetes Care	
	Breast Cancer Screening	Hemoglobin A1c (HbA1c) Testing		
Effect of MA enrollment	-27.5 (7.4)		-22.6 (10.3)	
Post-65 FFS baseline per 1,000 beneficiaries	484		937	
Percent change	-5.7%		-2.4%	
# Individuals	49,995		13,626	

Notes: The top panel of this table presents estimates of the effect of MA on hospitalizations for enrollees enrolled in MA HMO plans, where the cause of the hospitalization was a preventable complication of an existing condition, as measured using definitions provided by the Agency for Healthcare Research and Quality. The middle panel of this table presents estimates of the effect of MA on outcomes related to medication adherence and treatment appropriateness. Outcomes are constructed based on the standard Healthcare Effectiveness Data and Information Set (HEDIS) measures. The “Medication Adherence” columns represent estimates of effect of MA on whether patients with a diagnosis use corresponding prescriptions. The “High-risk Medication” column represents estimates of effect of MA on whether patients use high-risk medication. The “Alcohol/Drug Treatment” columns represent estimates of effect of MA on whether patients initiate or engage in treatment. The lower panel of this table presents estimates of the effect of MA on outcomes related to breast cancer screening and diabetes care, identified by HEDIS measures. The “Breast Cancer Screening” column presents estimates of effect of MA on whether female patients receive breast cancer screening. The “Diabetes Care” column presents estimates of effect of MA on whether patients receive Hemoglobin A1c (HbA1c) Testing. Regression estimates are based on our preferred specification described in Equation (1), with the exception of “Alcohol/Drug Treatment” outcomes where we use the same specification as in Table 2 Column (5) without matching due to substantial sample loss. Changes in percentage points are rescaled estimates in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the utilization at age 65 of the matched FFS cohort.

Appendix Table A13: Regression Analysis: Effects of MA on Quality Measures: MA PPO

	Preventable Complications		
	Overall	Acute	Chronic
Effect of MA enrollment	-2.05 (1.4)	-0.45 (0.9)	-1.74 (1.1)
Post-65 FFS baseline per 1,000 beneficiaries	6.30	2.49	4.06
Percent change	-32.5%	-18.2%	-42.8%
# Individuals	38,063	38,063	38,063

	Medication Adherence			Treatment Appropriateness		
	Hypertension	Diabetes	Cholesterol	High-risk Medication Usage	Alcohol and Other Drug Initiation	Engagement
Effect of MA enrollment	-22.0 (14.9)	-8.75 (39.3)	-14.48 (14.3)	-29.6 (6.97)	-84.3 (97.0)	108.4 (75.0)
Post-65 FFS baseline per 1,000 beneficiaries	854	847	834	229	856	118
Percent change	-2.6%	-1.0%	-1.7%	-12.9%	-9.9%	92.2%
# Individuals	12,785	4,486	15,241	37,315	343	343

	Preventive Screenings		Diabetes Care
	Breast Cancer Screening	Hemoglobin A1c (HbA1c) Testing	
Effect of MA enrollment	-46.3 (8.7)		-69.5 (15.6)
Post-65 FFS baseline per 1,000 beneficiaries	536		959
Percent change	-8.6%		-7.2%
# Individuals	23,223		6,079

Notes: The top panel of this table presents estimates of the effect of MA on hospitalizations for enrollees enrolled in MA PPO plans, where the cause of the hospitalization was a preventable complication of an existing condition, as measured using definitions provided by the Agency for Healthcare Research and Quality. The middle panel of this table presents estimates of the effect of MA on outcomes related to medication adherence and treatment appropriateness. Outcomes are constructed based on the standard Healthcare Effectiveness Data and Information Set (HEDIS) measures. The “Medication Adherence” columns represent estimates of effect of MA on whether patients with a diagnosis use corresponding prescriptions. The “High-risk Medication” column represents estimates of effect of MA on whether patients use high-risk medication. The “Alcohol/Drug Treatment” columns represent estimates of effect of MA on whether patients initiate or engage in treatment. The lower panel of this table presents estimates of the effect of MA on outcomes related to breast cancer screening and diabetes care, identified by HEDIS measures. The “Breast Cancer Screening” column presents estimates of effect of MA on whether female patients receive breast cancer screening. The “Diabetes Care” column presents estimates of effect of MA on whether patients receive Hemoglobin A1c (HbA1c) Testing. Regression estimates are based on our preferred specification described in Equation (1), with the exception of “Alcohol/Drug Treatment” outcomes where we use the same specification as in Table 2 Column (5) without matching due to substantial sample loss. Changes in percentage points are rescaled estimates in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the utilization at age 65 of the matched FFS cohort.

Appendix Table A14: Regression Analysis: Effects of MA on Low- and High-value of Care

	CT scan of acute sinusitis	Head imaging for uncomplicated headache	Back imaging for non-specific low back pain	Spine injection for non-specific low back pain	Antibiotics for acute respiratory infection
Low-value Care					
Effect of MA enrollment	-0.0735 (0.015)	0.0977 (0.036)	-0.0768 (0.023)	-0.0311 (0.016)	0.1196 (0.017)
Post-65 FFS baseline	0.052	0.21	0.38	0.11	0.48
Percent change	-140.5%	46.5%	-20.3%	-28.8%	25.0%
# Individuals	30,744	18,646	36,060	36,060	126,156
High-value Care					
	Antidepressant	Diabetes	Hypertension	Statin	
Effect of MA enrollment	0.243 (0.0088)	0.142 (0.0052)	0.387 (0.0061)	0.322 (0.0051)	
Post-65 FFS baseline	0.36	0.26	0.38	0.18	
Percent change	67.3%	55.2%	100.7%	182.2%	
# Individuals	126,478	126,853	129,513	129,951	

Notes: This table presents estimates of the effect of MA on outcomes related to low- and high-value of care used in the prior literature (Schwartz et al. 2014, Brot-Goldberg et al. 2017, Curto et al. 2019). Regression estimates are based on the specification described in Equation (1). Changes in percentage points are rescaled estimates in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the utilization at age 65 of the matched FFS cohort.

Appendix Table A15: Regression Analysis: Effects of MA on Low- and High-value of Care: MA HMO

	CT scan of acute sinusitis	Head imaging for uncomplicated headache	Back imaging for non-specific low back pain	Spine injection for non-specific low back pain	Antibiotics for acute respiratory infection
Low-value Care					
Effect of MA enrollment	-0.0860 (0.020)	0.0158 (0.045)	-0.1341 (0.034)	-0.0462 (0.024)	0.0976 (0.022)
Post-65 FFS baseline	0.057	0.22	0.41	0.12	0.49
Percent change	-151.8%	7.2%	-32.4%	-38.6%	19.9%
# Individuals	17,811	10,399	20,777	20,777	76,241
High-value Care					
	Antidepressant	Diabetes	Hypertension	Statin	
Effect of MA enrollment	0.184 (0.0112)	0.139 (0.0064)	0.365 (0.0077)	0.296 (0.0060)	
Post-65 FFS baseline	0.36	0.24	0.38	0.18	
Percent change	50.9%	57.1%	95.3%	166.0%	
# Individuals	76,358	76,623	78,195	78,473	

Notes: This table presents estimates of the effect of MA on outcomes related to low- and high-value of care used in the prior literature (Schwartz et al. 2014, Brot-Goldberg et al. 2017, Curto et al. 2019) for MA HMO plans. Regression estimates are based on the specification described in Equation (1). Changes in percentage points are rescaled estimates in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the utilization at age 65 of the matched FFS cohort.

Appendix Table A16: Regression Analysis: Effects of MA on Low- and High-value of Care: MA PPO

	CT scan of acute sinusitis	Head imaging for uncomplicated headache	Back imaging for non-specific low back pain	Spine injection for non-specific low back pain	Antibiotics for acute respiratory infection
Low-value Care					
Effect of MA enrollment	-0.0367 (0.023)	0.0417 (0.064)	0.0126 (0.042)	-0.0747 (0.027)	0.1776 (0.020)
Post-65 FFS baseline	0.041	0.22	0.35	0.09	0.47
Percent change	-88.9%	18.7%	3.6%	-82.8%	37.8%
# Individuals	35,482	35,604	36,495	36,619	35,316
High-value Care					
	Antidepressant	Diabetes	Hypertension	Statin	
Effect of MA enrollment	0.319 (0.0129)	0.164 (0.0079)	0.406 (0.0086)	0.328 (0.0077)	
Post-65 FFS baseline	0.36	0.28	0.39	0.18	
Percent change	88.2%	58.1%	103.6%	182.9%	
# Individuals	10,392	10,392	4,779	8,313	

Notes: This table presents estimates of the effect of MA on outcomes related to low- and high-value of care used in the prior literature (Schwartz et al. 2014, Brot-Goldberg et al. 2017, Curto et al. 2019) for MA PPO plans. Regression estimates are based on the specification described in Equation (1). Changes in percentage points are rescaled estimates in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the utilization at age 65 of the matched FFS cohort.

Appendix Table A17: Poisson Regression: Heterogeneity in Utilization Effects of MA by Future MA Plan Type

	HMO	PPO
Effect of MA enrollment	-0.158 (0.035)	-0.0085 (0.092)
Pre-65 Risk adjusted?	✓	✓
Using pre-65 data?	✓	✓
Poisson?	✓	✓

Notes: This table presents estimates of the effects of MA enrollment on total health care utilization based on Poisson regression specification by future MA plan type. For all estimates, the outcome is the percent change in the quarterly total allowed spending.

Appendix Table A18: Heterogeneity in Utilization Effects of MA by Future MA Plan Characteristics

	HMO	PPO	Urban	Non-urban
Effect of MA enrollment	-331.7 (49.4)	102.0 (100.3)	-158.5 (53.6)	-43.3 (106.9)
Post-65 FFS baseline	\$1,996	\$2,105	\$2,021	\$2,046
Percent change	-16.6%	4.8%	-7.8%	-2.1%
# Individuals	84,127	39,400	95,985	40,262

	Star Ratings (overall)			
	≤ 3.0	3.5	4.0	≥ 4.5
Effect of MA enrollment	-342.6 (130.1)	-454.2 (92.1)	23.4 (91.3)	-259.5 (74.9)
Post-65 FFS baseline	\$2,038	\$1,994	\$2,079	\$2,013
Percent change	-16.8%	-22.8%	1.1%	-12.9%
# Individuals	11,250	29,146	36,703	42,441

	MA Penetration Rate Quartiles			
	Q1	Q2	Q3	Q4
Effect of MA enrollment	-875.8 (475.9)	-372.3 (164.6)	-449.5 (102.9)	-101.9 (73.0)
Post-65 FFS baseline	\$2,194	\$2,166	\$1,977	\$2,079
Percent change	-39.9%	-17.2%	-22.7%	-4.9%
# Individuals	256	4,474	12,443	55,139

	State MA HHI Below Median	State MA HHI Above Median
Effect of MA enrollment	-165.5 (52.2)	-1.10 (119.2)
Post-65 FFS baseline	\$2,004	\$2,097
Percent change	-8.3%	-0.1%
# Individuals	101,503	34,744

Notes: This table presents coefficient estimates of the effect of MA on utilization by MA plan characteristics. Our measure of utilization is quarterly total allowed spending, with prices normalized to FFS reimbursement rates. MA penetration rates are calculated at the 3-digit ZIP Code level by dividing the number of MA enrollees (Inovalon) by the total number of MA enrollees (Inovalon) and FFS enrollees. Thresholds MA penetration rate quartiles are determined based on the all unique 3-digit ZIP Code-penetration rates that we observe in the analytical sample. Regression estimates are based on the specification described in Equation (1). Changes in percentage points are rescaled estimates in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the average quarterly total health care spending at age 65 of the matched FFS cohort.

Appendix Table A19: Favorable Selection of Future MA Enrollees by Type of Service

	Inpatient	Observation stay	ED	Outpatient	Physician office	Post-acute care	Rx
MA_i	17.68 (10.1)	-2.95 (1.65)	-5.00 (1.31)	-116.8 (8.93)	-19.87 (0.91)	13.29 (5.51)	-55.57 (33.9)
Pre-65 FFS baseline	\$227	\$11.2	\$39.9	\$512	\$110	\$32.4	\$460
Percent change	7.8%	-26.4%	-12.5%	-22.8%	-18.0%	41.0%	-12.1%
# Individuals	205,557	205,557	205,557	205,557	205,557	205,557	205,557

Notes: These tables present coefficient estimates of the favorable selection of future MA enrollees by type of services. Our measure of costliness is allowed quarterly spending at age 64 for each type of service, with prices normalized to FFS reimbursement rates. Regression estimates are based on the specification described in Equation (2) controlling for risk scores at age 64, cohort-market fixed effects. Changes in percentage points are rescaled estimates by control means based on the average quarterly spending of each type of service at age 64 of the FFS cohort.

Appendix Table A20: Heterogeneity in Favorable Selection of Future MA Enrollees by Enrollee Characteristics

	Female	Male	White	Non-white
MA_i	-188.0 (56.1)	-229.0 (49.4)	-157.5 (44.6)	-182.9 (41.8)
Pre-65 FFS baseline	\$1,796	\$1,881	\$1,841	\$1,830

	Percent change	-10.5%	-12.2%	-8.6%	-10.0%
# Individuals	123,464	82,093	182,505	195,925	

	Income Quartiles			
	Q1	Q2	Q3	Q4
MA_i	-259.4 (53.7)	-70.8 (129.8)	-242.2 (68.0)	-175.1 (45.8)
Pre-65 FFS baseline	\$1,921	\$1,841	\$1,826	\$1,781
Percent change	-13.5%	-3.8%	-13.3%	-9.8%
# Individuals	40,069	40,379	46,327	68,859

	RAF Terciles		
	T1	T2	T3
MA_i	-117.6 (42.1)	-69.0 (63.5)	-437.7 (74.5)
Pre-65 FFS baseline	\$651	\$805	\$3,687
Percent change	-18.1%	-8.6%	-11.9%
# Individuals	46,195	84,911	74,451

Notes: These tables present coefficient estimates of the favorable selection of future MA enrollees by enrollee characteristics. Our measure of costliness is allowed quarterly spending at age 64 for each type of service, with prices normalized to FFS reimbursement rates. Regression estimates in the upper panel are based on our preferred specification Equation (2) controlling for risk scores at age 64, gender, cohort-market fixed effects. Changes in percentage points are rescaled estimates by control means based on the average quarterly spending of each type of service at age 64 of the FFS cohort. Income quartiles are determined based on average income in the individual's 9-digit zip code at age 64. Risk score terciles are determined based on CMS-HCC risk scores measured at age 64.

Appendix Table A21: Heterogeneity in Favorable Selection of Future MA Enrollees: HCC High-Level Groupings

	Neoplasm	Diabetes	Liver	Blood	SA
MA_i	-553.5 (251.9)	-323.0 (88.7)	-147.6 (844.6)	-611.5 (558.2)	-888.3 (584.4)
Pre-65 FFS baseline	\$5,463	\$3,257	\$7,304	\$8,212	\$5,543
Percent change	-10.1%	-9.9%	-2.0%	-7.4%	-16.0%
# Individuals	15,857	30,058	1,637	5,245	2,087
	Psychiatric	Spinal	Arrest	Heart	CVD
MA_i	-551.6 (274.8)	872.2 (2002.4)	-636.2 (1286.2)	-359.7 (192.4)	-442.9 (488.6)
Pre-65 FFS baseline	\$3,625	\$8,501	\$13,723	\$4,917	\$6,711
Percent change	-15.2%	10.3%	-4.6%	-7.3%	-6.6%
# Individuals	8,247	661	1,619	16,106	1,741
	Vascular	Lung	Kidney	Skin	Injury
MA_i	-422.9 (304.5)	-678.9 (285.5)	-616.3 (766.5)	-338.9 (752.1)	105.9 (782.6)
Pre-65 FFS baseline	\$5,709	\$5,100	\$9,814	\$7,989	\$7,711
Percent change	-7.4%	-13.3%	-6.3%	-4.2%	1.4%
# Individuals	7,851	8,600	2,838	1,025	1,623

Notes: These tables present coefficient estimates of the favorable selection of future MA enrollees by HCC high-level groupings. Our measure of costliness is allowed quarterly spending at age 64 for each type of service, with prices normalized to FFS reimbursement rates. Regression estimates in the upper panel are based on our preferred specification Equation (2) controlling for risk scores at age 64, cohort-market fixed effects. Changes in percentage points are rescaled estimates by control means based on the average quarterly spending of each type of service at age 64 of the FFS cohort. "SA" stands for substance abuse. "CVD" stands for cerebrovascular disease.

Appendix Table A22: Heterogeneity in Favorable Selection of Future MA Enrollees by Plan Characteristics

	Low Rebates		High Rebates			
	HMO	PPO	Premium=0	Premium>0	Premium=0	Premium>0
MA_i	-308.8 (30.9)	-25.9 (115.1)	-34.1 (105.0)	11.2 (90.0)	-443.0 (33.6)	-330.3 (76.5)
Post-65 FFS baseline	\$1,830	\$1,830	\$1,830	\$1,830	\$1,830	\$1,830
Percent change	-16.9%	-1.4%	-1.9%	0.6%	-24.2%	-18.1%
# Individuals	195,844	187,356	181,779	188,900	188,046	184,649

	Low Rebates		High Rebates		Star Ratings (overall)	
	HMO	PPO	HMO	PPO	≤ 3.0	3.5
MA_i	-105.8 (53.1)	107.4 (146.4)	-407.8 (35.4)	-392.8 (135.3)	-276.8 (65.3)	-43.9 (157.3)
Post-65 FFS baseline	\$1,830	\$1,830	\$1,830	\$1,830	\$1,830	\$1,830
Percent change	-5.8%	5.9%	-22.3%	-21.5%	-15.1%	-2.4%
# Individuals	185,330	185,349	190,601	182,094	182,168	185,561

	Star Ratings (overall)		MA Penetration Rate Quartiles			
	4.0	≥ 4.5	Q1	Q2	Q3	Q4
MA_i	-167.6 (53.1)	-374.6 (43.6)	-439.8 (154.8)	-406.1 (81.9)	-209.6 (72.8)	-238.7 (46.5)
Post-65 FFS baseline	\$1,830	\$1,830	\$1,745	\$1,865	\$1,834	\$1,938
Percent change	-9.2%	-20.5%	-25.2%	-21.8%	-11.4%	-12.3%
# Individuals	186,872	188,046	10,654	25,682	25,653	35,287

	State MA HHI			
	Urban	Non-urban	Below median	Above median
MA_i	-277.9 (33.5)	-25.9 (108.2)	-252.0 (32.3)	-61.4 (115.2)
Post-65 FFS baseline	\$1,878	\$1,749	\$1,779	\$1,978
Percent change	-14.8%	-1.5%	-14.2%	-3.1%
# Individuals	130,833	74,724	153,292	52,265

Notes: These tables present coefficient estimates of the favorable selection of future MA enrollees by MA plan characteristics. MA penetration rates are calculated at the 3-digit ZIP Code level by dividing the number of MA enrollees (Inovalon) by the total number of MA enrollees (Inovalon) and FFS enrollees. Our measure of costliness is allowed quarterly spending at age 64 for each type of service, with prices normalized to FFS reimbursement rates. Regression estimates in the upper panel are based on our preferred specification Equation (2) controlling for risk scores at age 64, cohort-market fixed effects. Changes in percentage points are rescaled estimates by control means based on the average quarterly spending of each type of service at age 64 of the FFS cohort.

B Estimates for Longer Panels

In our primary estimates, we focus on short panels analyzing four quarters before and after qualifying Medicare by turning 65. In this appendix, we extend our analysis to subsamples where we can observe beneficiaries for longer periods of time before and/or after turning 65.

For each subsample, we construct it by starting with our initial sample, and conditioning on being able to observe continuous enrollment in either employer-sponsored or Medicare coverage for the target length of time. For empirical analysis, when matching, we use the propensity scores constructed from the model estimated on the entire sample, but rematch treated beneficiaries to five control beneficiaries *within* the restricted subsample. We then truncate our observation window to the same period used for subsample selection.

Appendix Tables **B1** and **B2** display summary statistics for these subsamples, and, for each subsample, our primary regression estimating the effect of MA on utilization. Appendix Table **B2** also includes a specification where we interact the treatment status with the enrollee's age, to estimate separate effects of MA at ages 65, 66, and 67 (the first three years of enrollment). All other figures and tables in this section are estimated using the subsample where we observe two years before and after Medicare enrollment.

Appendix Table B1: Sample Robustness under Different Panel Lengths

Years Pre-65	1	1	1	2	2	3
Years Post-65	1	2	3	1	2	1
Future MA						
% Female	0.58	0.59	0.58	0.57	0.57	0.57
% White	0.91	0.91	0.91	0.92	0.92	0.95
% Urban	0.71	0.70	0.70	0.70	0.70	0.69
% HMO Prior Medicare	0.46	0.47	0.48	0.39	0.41	0.36
% PPO Prior Medicare	0.43	0.42	0.42	0.50	0.49	0.55
Avg. Qtr. Spending at 64	\$1,464	\$1,468	\$1,457	\$1,467	\$1,439	\$1,457
Avg. Qtr. Spending at 65	\$1,634	\$1,655	\$1,661	\$1,618	\$1,658	\$1,595
# Individuals	25,470	19,178	15,242	15,608	11,549	8,998
Future FFS						
% Female	0.60	0.60	0.61	0.60	0.60	0.60
% White	0.96	0.96	0.96	0.96	0.96	0.96
% Urban	0.66	0.66	0.66	0.67	0.67	0.68
% HMO Prior Medicare	0.28	0.28	0.27	0.25	0.24	0.25
% PPO Prior Medicare	0.57	0.57	0.57	0.61	0.61	0.59
Avg. Qtr. Spending at 64	\$1,830	\$1,784	\$1,748	\$1,856	\$1,794	\$1,862
Avg. Qtr. Spending at 65	\$2,194	\$2,115	\$2,065	\$2,149	\$2,158	\$2,121
# Individuals	180,087	173,354	166,194	121,199	117,059	64,687

Notes: This table presents summary statistics for samples under different panel lengths. Our measures of average quarterly spending at age 64 and 65 are price-adjusted by equivalent reimbursement rates in the FFS program. “Years Pre-65” means the number of continuous enrollment years in ESHI prior to age 65. “Years Post-65” means the number of continuous enrollment years in MA or FFS since age 65. “Future MA” enrollees are enrollees who enrolled in Medicare Advantage plans captured by Inovalon. Sample sizes are calculated based on panel length restriction consisting of future MA and FFS enrollees.

Appendix Table B2: Estimation Robustness under Different Panel Lengths

	Samples					
Years Pre-65	1	1	1	2	2	3
Years Post-65	1	2	3	1	2	1
Effect of MA enrollment	-124.9 (49.1)	-157.1 (41.9)	-196.3 (43.0)	-149.8 (49.0)	-246.2 (109.4)	-179.5 (62.5)
Post-65 FFS baseline	\$2,028	\$2,015	\$2,044	\$1,954	\$2,087	\$1,921
Percent change	-6.2%	-7.8%	-9.6%	-7.7%	-11.8%	-9.3%
$MA_i \times Age65$	-124.9 (49.1)	-99.2 (55.1)	-81.2 (61.7)	-149.8 (49.0)	-111.4 (61.6)	-179.5 (62.5)
Age 65 FFS baseline	\$2,028	\$1,973	\$1,950	\$2,149	\$1,957	\$2,121
Percent change	-6.2%	-5.0%	-4.2%	-7.0%	-5.7%	-8.5%
$MA_i \times Age66$		-201.10 (56.0)	-179.16 (59.1)			-380.95 (189.7)
Age 66 FFS baseline		\$2,057	\$2,000			\$2,217
Percent change		-9.8%	-9.0%			-17.2%
$MA_i \times Age67$			-405.64 (65.1)			
Age 67 FFS baseline				\$2,183		
Percent change				-18.6%		
# Individuals	136,247	101,660	81,291	82,931	60,670	47,353

Notes: This table presents estimates of the effects of Medicare Advantage enrollment on total health care utilization under samples with different panel lengths. For all estimates, the outcome is quarterly total allowed spending, with prices normalized to FFS reimbursement rates. Regression estimates are based on the specification described in Equation (1). Changes in percentage points are rescaled estimates in terms of estimated percent change due to enrollment in MA. “Years Pre-65” means the number of continuous enrollment years in ESHI prior to age 65. “Years Post-65” means the number of continuous enrollment years in MA or FFS since age 65. Sample sizes are calculated based on panel length restriction consisting of future MA and FFS enrollees.

Appendix Table B3: Effects of MA on Total Health Care Utilization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Effect of MA enrollment	-581.3 (41.4)	-394.0 (38.8)	-378.8 (100.5)	-117.6 (48.6)	-144.2 (37.4)	-173.7 (49.1)	-246.2 (109.4)
Post-65 FFS baseline	\$2,158	\$2,158	\$2,087	\$2,158	\$2,158	\$2,158	\$2,087
Percent change	-26.9%	-18.3%	-18.1%	-5.5%	-6.7%	-8.1%	-11.8%
Risk adjusted?		✓	✓	✓			
Using pre-65 data?				✓	✓	✓	✓
Individual FEs?					✓	✓	✓
Plan Characteristics FEs?						✓	✓
Matching?			✓				✓
# Individuals	114,057	114,057	60,670	114,057	128,608	128,608	60,670

Notes: This table presents coefficient estimates of the effects of Medicare Advantage enrollment on total health care utilization based on our extended panel requiring continuous enrollments eight quarters prior and post age 65. For all estimates, the outcome is quarterly total allowed spending, with prices normalized to FFS reimbursement rates. Column 7 presents our preferred specification described in Equation (1). Changes in percentage points are rescaled estimates in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the average quarterly total health care utilization at age 65 and 66 of the unmatched FFS cohort from columns 1, 2, 4, 5 and 6 and matched FFS cohort for column 3 and 7.

Appendix Table B4: Heterogeneity in Utilization Effects of MA by Type of Service

	Inpatient	Observation stay	ED	Outpatient	Physician office	Post-acute Care	Rx
Prevalence	-0.00593 (0.00094)	-0.00175 (0.00054)	-0.00712 (0.00144)	-0.0182 (0.00348)	-0.0350 (0.00367)	0.631621 (1.67035)	0.63 (1.67)
Post-65 FFS baseline	0.021921	0.00769	0.04815	0.737	0.659	0.00818	248.6
Percent change	-27.0%	-22.7%	-14.8%	-2.5%	-5.3%	7721.5%	0.3%
Cost	-102.0 (26.5)	6.06 (2.40)	6.0 (2.46)	21.82 (69.9)	-15.47 (2.72)	-14.8 (7.15)	-70.8 (33.6)
Post-65 FFS baseline	\$403	\$9.06	\$45.4	\$747	\$178	\$56.0	\$453
Percent change	-25.3%	66.9%	13.1%	2.9%	-8.7%	-26.4%	-15.6%
# Individuals	60,670	60,670	60,670	60,670	60,670	60,670	60,670

Notes: This table presents estimates of the effect of MA on utilization of specific services based on our extended panel requiring continuous enrollments eight quarters prior and post age 65. For all estimates in the “Prevalence” section (upper panel), the outcome is whether or not the beneficiary ever used the type of service in a given quarter, except the final outcome, which is the total days supply of all prescription drugs used by the beneficiary. For all estimates in the “Cost” section (lower panel), the outcome is quarterly total allowed spending, with prices normalized to FFS reimbursement rates. Regression estimates are based on the specification described in Equation (1). Estimates are rescaled in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the quarterly average prevalence or total health care spending at age 65 and 66 of the matched FFS cohort.

Appendix Table B5: Favorable Selection of Future MA Enrollees

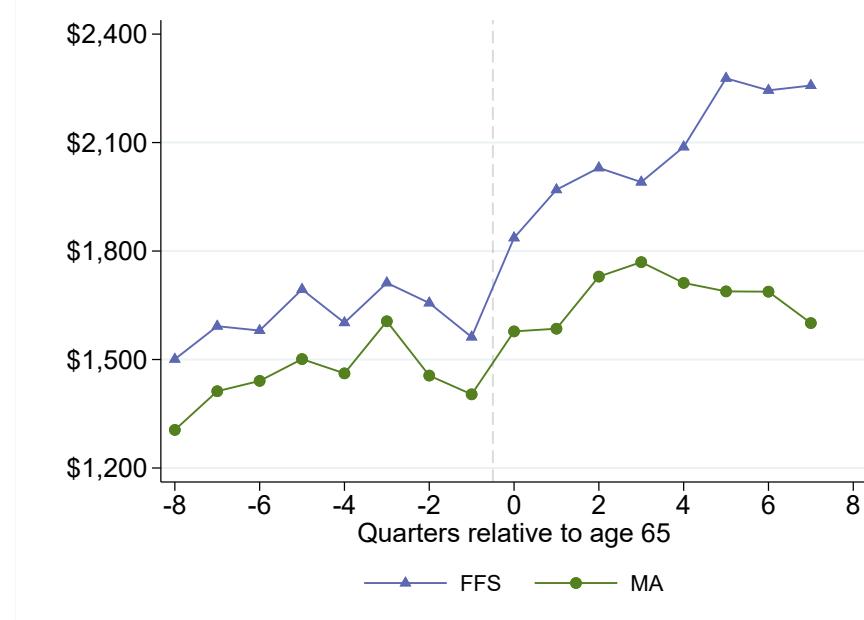
	(1)	(2)	(3)	(4)	(5)	(6)
MA_i	-355.6 (32.2)	-218.7 (28.3)	-220.1 (34.2)	-204.6 (34.0)	-174.7 (36.4)	-159.3 (37.1)
Pre-65 FFS baseline	\$1,794	\$1,794	\$1,794	\$1,794	\$1,794	\$1,794
Percent change	-19.8%	-12.2%	-12.3%	-11.4%	-9.7%	-8.9%
Risk scores?	✓	✓	✓	✓	✓	✓
Gender?	✓	✓	✓	✓	✓	✓
Cohort-market FEs?		✓	✓	✓	✓	✓
Richer diagnosis FEs?			✓	✓	✓	✓
Race/Urban?				✓	✓	✓
SDOH?					✓	
# Individuals	128,608	128,608	128,608	128,608	114,057	112,856

Notes: This table presents coefficient estimates of the favorable selection of future MA enrollees based on our extended panel requiring continuous enrollments eight quarters prior and post age 65. Our measure of costliness is total allowed quarterly spending at age 63 and 64, with prices normalized to FFS reimbursement rates. Column (3) presents estimates based on our preferred specification equation (2). Changes in percentage points are rescaled estimates by control means based on the average quarterly total health care spending at age 63 and 64 of the FFS cohort.

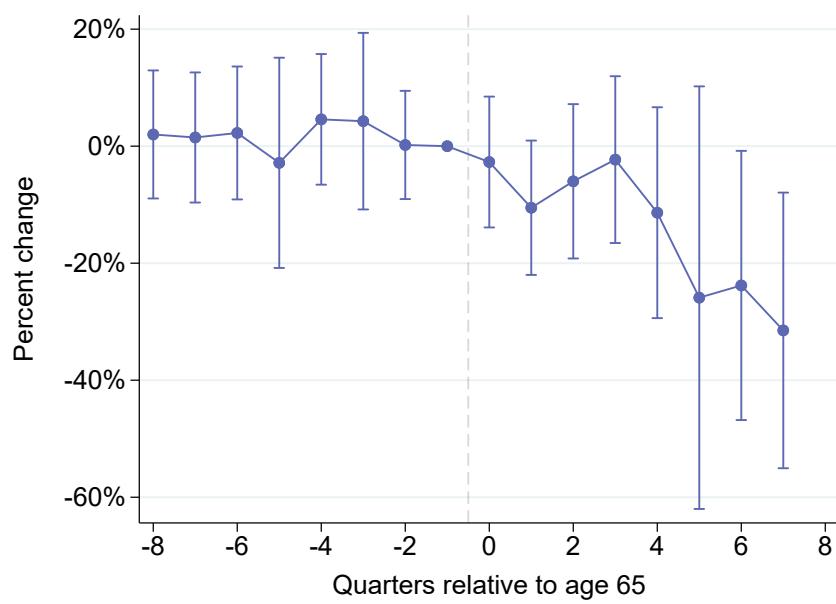
Appendix Table B6: Favorable Selection of Future MA Enrollees by Type of Service

	Inpatient Visits	Observation Stays	Emergency Department	Outpatient Visits	Physician Office	Post Acute Care	Rx
MA_i	14.77 (11.3)	-0.94 (1.66)	-3.84 (1.45)	-120.5 (9.49)	-22.36 (1.19)	4.15 (4.27)	-60.99 (27.4)
Pre-65 FFS baseline	\$236	\$11.3	\$39.6	\$523	\$108	\$25.4	\$424
Percent change	6.3%	-8.4%	-9.7%	-23.1%	-20.7%	16.4%	-14.4%
# Individuals	128,608	128,608	128,608	128,608	128,608	128,608	128,608

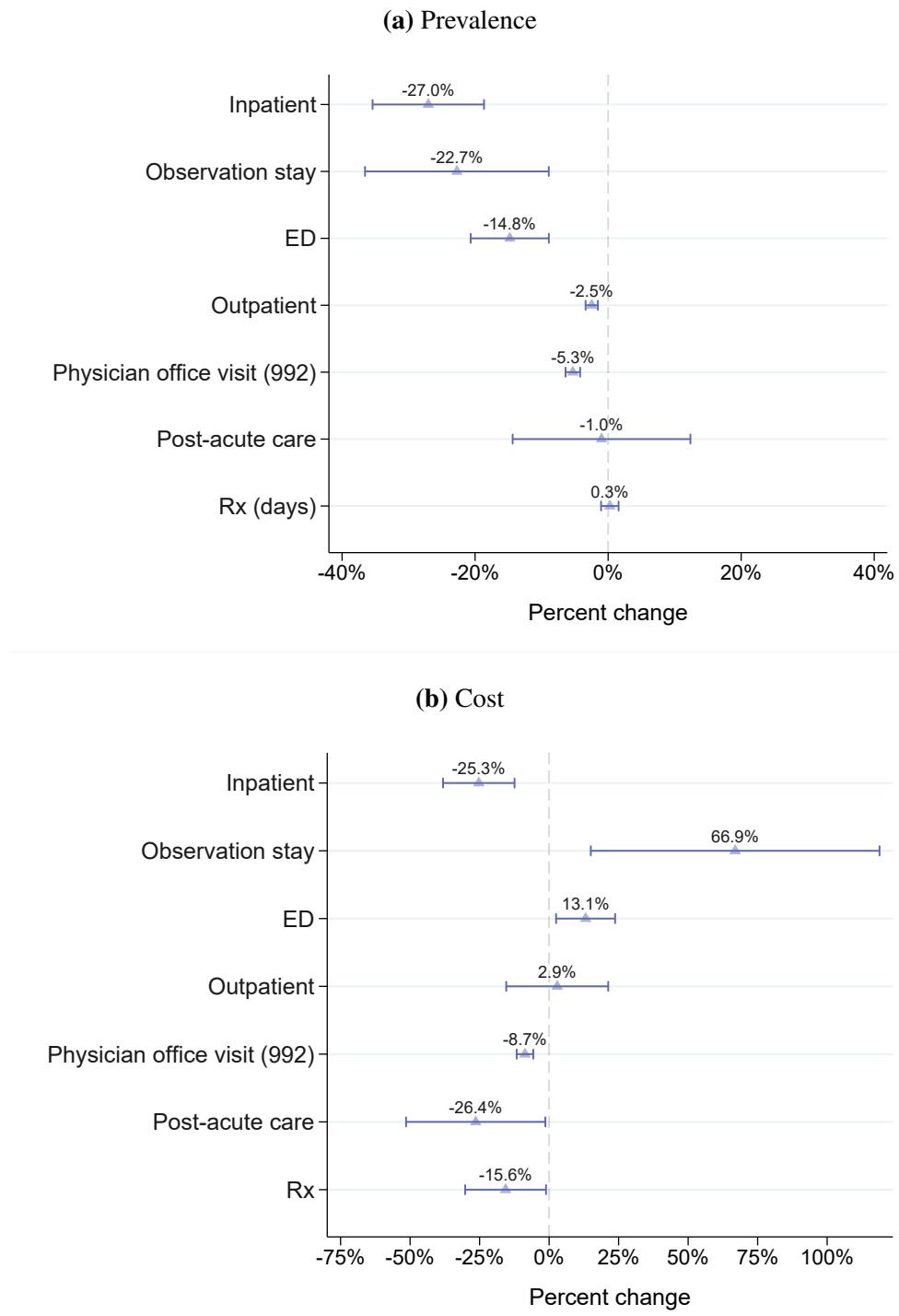
Notes: This table presents coefficient estimates of the favorable selection of future MA enrollees by type of services based on our extended panel requiring continuous enrollments eight quarters prior and post age 65. Our measure of costliness is allowed quarterly spending at age 63 and 64 for each type of service, with prices normalized to FFS reimbursement rates. Regression estimates are based on the specification described in Equation (2) controlling for risk scores at age 64, cohort-market fixed effects. Changes in percentage points are rescaled estimates by control means based on the average quarterly spending of each type of service at age 63 and 64 of the FFS cohort.

Appendix Figure B1: Quarterly Total Health Care Utilization around Medicare Enrollments

Notes: This figure presents the average quarterly health care utilization for beneficiaries in our longer event time sample requiring continuous enrollments eight quarters prior and post age 65 with the matching strategy described in Section 3.1. Our measure of utilization is quarterly total allowed spending, with prices normalized to FFS reimbursement rates. The two lines represent the time series for the group of individuals who (eventually) enroll in Traditional FFS Medicare (in purple) and in Medicare Advantage (in green). For each individual, quarters are indexed relative to the quarter that the individual turned 65 and qualified to enroll in Medicare (on the horizontal axis).

Appendix Figure B2: Event Study Estimates of the Utilization Effects of MA

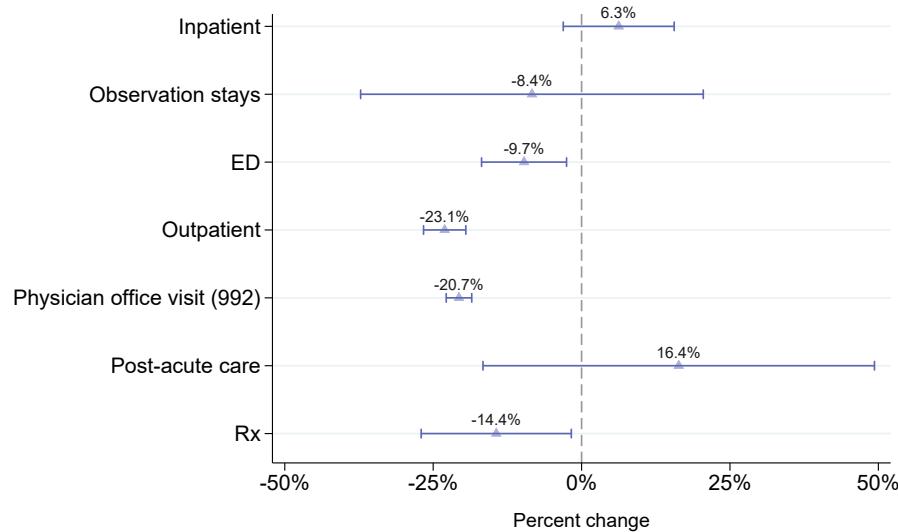
Notes: This figure presents event study estimates of the treatment effect of Medicare Advantage on overall health care utilization based on our extended panel requiring continuous enrollments eight quarters prior and post age 65. Our measure of utilization is quarterly total allowed spending, with prices normalized to FFS reimbursement rates. For each individual, quarters are indexed relative to the quarter that the individual turned 65 and qualified to enroll in Medicare (on the horizontal axis). Regression estimates are based on the specification described in Equation (1). Estimates are rescaled in terms of estimated percent change in utilization relative to utilization in the quarter before turning 65.

Appendix Figure B3: Heterogeneity in Utilization Effects of MA by Type of Service

Notes: These figures present estimates of the effect of MA on utilization of specific services based on our extended panel requiring continuous enrollments eight quarters prior and post age 65. Each mark represents a different utilization outcome, for a given subset of health care services. The outcome in the upper panel is whether or not the beneficiary ever used the type of service in a given quarter, except the final outcome, which is the total days supply of all prescription drugs used by the beneficiary; the outcome in the lower panel is utilization, measured as quarterly total allowed spending with prices normalized to FFS reimbursement rates. Regression estimates are based on the specification described in Equation (1). Estimates are presented in terms of estimated percent change relative to average utilization of FFS enrollees at age 65.

Underlying estimates are given in Appendix Table B4.

Appendix Figure B4: Heterogeneity in Favorable Selection of Future MA Enrollees by Type of Service



Notes: These figures present estimates of the favorable selection of future MA enrollees of specific services based on our extended panel requiring continuous enrollments eight quarters prior and post age 65. Each bar represents a selection estimate using a different type of service as the outcome. For all estimates, utilization is measured as quarterly total allowed spending with prices normalized to FFS reimbursement rates. Regression estimates in the upper-panel are based on specification Equation (2) controlling for risk scores at age 64, gender and cohort-market fixed effects. Estimates are presented in terms of estimated percent change relative to average utilization of future FFS enrollees at age 64.

Underlying estimates are given in Appendix Table B6.

C Fiscal Cost Calculation Appendix

In Section 4, we assess the implications of MA for the fiscal cost of providing Medicare benefits to MA enrollees. This requires us to estimate both the current payments that CMS pays to MA plans on enrollees' behalf, as well as the counterfactual cost to CMS of enrolling MA enrollees in the FFS plan. We detail those here, as well as display constituent calculations used in our figures. As a reminder, for all cost construction, we construct for each beneficiary individually.

C.1 Constructing Current Costs of MA Enrollment

To compute current costs, we replicate CMS's capitation payment formula. Current costs have four major components: Base payments, rebates, quality bonus payments, and a net upcoding factor.

Constructing base payments starts with the risk-adjusted bid, $b_j r_i$, for beneficiary i and plan j . r_i reflects a beneficiary's risk score, which we compute using diagnoses as evaluated at age 64.³² Due to concerns about re-identification of specific plans, we only observe bids as ventile bins. We use the midpoint of the bin for each plan. CMS will only allow bids to count towards base payments up until the county benchmark B_i (indexed by the county of the beneficiary, i). Therefore, base payments from CMS to plans are $\min\{b_j r_i, B_i r_i\}$.

Next, we compute supplemental and bonus payments. First, plans receive rebates in exchange for bidding below the benchmark amounts. We compute the plan's rebate payments as $\max\{0.5(B_i - b_j)r_i, 0\}$, where 0.5 reflects the fact that, at baseline, plans receive 50% of the risk-adjusted bid-benchmark gap as rebate. Second, we compute quality bonus payments. CMS rewards MA plans for providing higher quality, measured in terms of their star ratings. Quality bonus payments come in two forms: First, plans with higher stars get receive higher rebates as a share of the risk-adjusted difference between their bid and the benchmark. Plans rated 3.5 or 4 stars have adjustment factors of 0.6 rather than 0.5, and plans rated 4.5 or 5 stars have adjustment factors of 0.7. Second, plans rated 4 stars or better receive benchmarks that are 5% higher.³³ We compute the rebate bonus as $\max\{(\alpha_j - 0.5)(B_i - b_j)r_i, 0\}$, where α_j is the plan-specific quality adjustment factor, and the benchmark bonus as $\max\{\alpha_j(B_{ij} - B_i)r_i, 0\} - (\max\{b_j - B_{ij}, 0\} - \max\{b_j - B_i, 0\})$, where B_{ij} is the plan-by-beneficiary-county-specific benchmark, which incorporates plan-specific benchmark increases.

Finally, we compute an upcoding factor. This accounts for the fact that, as [Geruso and Layton \(2020\)](#) document, MA plans tend to have greater coding than FFS, resulting in higher risk scores. Since our risk scores are computed at age 64, before actual MA enrollment, they do not include this upcoding factor. We calibrate additional current payments from CMS as $\theta [\min\{b_j r_i, B_i r_i\} + \max\{\alpha_j(B_{ij} - b_j)r_i, 0\}]$, where θ is the net upcoding factor. We calibrate from [Geruso and Layton \(2020\)](#) that upcoding inflates risk scores by 6.4%, while CMS adjusts MA risk scores down by 5.91% (as of 2018) to account for this, resulting in a

³²Technically, since CMS does not have access to diagnoses for new Medicare enrollees, an alternative formula is used for reimbursement in the first year of enrollment. We use the standard reimbursement formula such that our evaluation more reflects a "steady state" rather than the idiosyncrasies of this rule.

³³This benchmark bonus is doubled in urban counties with low FFS spending and high MA enrollment. We are not able to identify such "double bonus" counties. Nor can we identify new plans offered by an organization which has not had an MA contract in the three preceding years, which receive an additional benchmark increase of 3.5%.

net upcoding factor of 0.49% (0.0049).

C.2 Constructing Counterfactual Costs

We next compute counterfactual costs. We do so *only* for medical utilization, excluding prescription drug use, which is reimbursed separately and privatized even for those enrolled in FFS. We begin by re-estimating our measures of treatment effects excluding drug utilization, reported in Appendix Table C1. We apply the main treatment effect to our pooled sample; for any subsample, we re-estimate this regression and use the associated subsample-specific average treatment effect.

To estimate the beneficiary's counterfactual spending in FFS, we take the treatment effect and add it to the beneficiary's actual realized spending in MA. This spending is not fully internalized by CMS, however, since there is cost-sharing in the FFS program. CMS's actuarial value is 85% ([Ippolito et al. 2024](#)). Therefore, to convert spending into CMS costs, we multiply it by 0.85. Finally, when MA enrollees move to FFS, CMS will have to pay for the administrative costs of managing their insurance. Administrative costs in FFS Parts A and B are approximately 1.4 cents per dollar of spending ([Kaiser Family Foundation 2019](#)). We assume the same average rate to estimate administrative costs.

C.3 Supplemental Tables

Appendix Table C1: Effects of MA on Total Medical Care Utilization (One-year Estimates)

	All	HMO	PPO
Effect of MA enrollment	-145.5 (39.7)	-334.0 (41.1)	37.7 (66.7)
Pre-65 FFS baseline	\$1,610	\$1,579	\$1,660
Percent change	-9.0%	-21.2%	2.3%
# Individuals	136,247	84,127	39,400

	Low Rebates		High Rebates	
	Premium=0	Premium>0	Premium=0	Premium>0
Effect of MA enrollment	-66.7 (82.4)	65.8 (52.8)	-396.7 (56.1)	-480.1 (85.5)
Pre-65 FFS baseline	\$1,519	\$1,597	\$1,610	\$1,645
Percent change	-4.4%	4.1%	-24.6%	-29.2%
# Individuals	9,111	47,409	42,743	24,264

	Low Rebates		High Rebates	
	HMO	PPO	HMO	PPO
Effect of MA enrollment	-88.0 (53.7)	162.2 (74.0)	-454.0 (52.6)	-269.2 (131.5)
Pre-65 FFS baseline	\$1,557	\$1,611	\$1,591	\$1,591
Percent change	-5.7%	10.1%	-28.5%	-16.9%
# Individuals	28,017	28,503	56,110	10,897

	State MA HHI			
	Urban	Non-urban	Below median	Above median
Effect of MA enrollment	-161.2 (46.8)	-107.3 (74.7)	-163.3 (46.3)	-91.4 (76.6)
Pre-65 FFS baseline	\$1,644	\$1,596	\$1,596	\$1,652
Percent change	-9.8%	-6.7%	-10.2%	-5.5%
# Individuals	95,985	40,262	101,503	34,744

Notes: This table presents coefficient estimates of the effects of Medicare Advantage enrollment on total medical care utilization based on the main panel and extended panel requiring continuous enrollments eight quarters prior and post age 65. For all estimates, the outcome is quarterly total allowed medical care spending, with prices normalized to FFS reimbursement rates. Results based on our preferred specification Equation (1). Changes in percentage points are rescaled estimates in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the average quarterly total medical care spending at age 65 of the matched FFS cohort. “High rebate” is defined as plan payment rebates above median value; “low rebate” is defined as plan payment rebates below median value.

Appendix Table C2: Effects of MA on Total Medical Care Utilization (Two-year Estimates)

	All	HMO	PPO
Effect of MA enrollment	-175.3 (90.4)	-419.5 (153.0)	99.8 (67.0)
Pre-65 FFS baseline	\$1,634	\$1,686	\$1,596
Percent change	-10.7%	-24.9%	6.3%
# Individuals	60,670	20,708	11,750

	Low Rebates		High Rebates	
	Premium=0	Premium>0	Premium=0	Premium>0
Effect of MA enrollment	-104.1 (110.1)	75.4 (57.4)	-477.8 (262.1)	-400.1 (88.3)
Pre-65 FFS baseline	\$1,435	\$1,581	\$1,778	\$1,640
Percent change	-7.3%	4.8%	-26.9%	-24.4%
# Individuals	2,557	20,853	18,059	11,377

	Low Rebates		High Rebates	
	HMO	PPO	HMO	PPO
Effect of MA enrollment	-118.1 (67.2)	155.3 (74.2)	-535.4 (208.4)	-45.2 (136.0)
Pre-65 FFS baseline	\$1,554	\$1,574	\$1,742	\$1,742
Percent change	-7.6%	9.9%	-30.7%	-2.6%
# Individuals	9,997	13,413	23,908	5,528

	State MA HHI			
	Urban	Non-urban	Below median	Above median
Effect of MA enrollment	-244.7 (124.5)	-13.6 (81.0)	-244.0 (118.6)	24.0 (77.5)
Pre-65 FFS baseline	\$1,551	\$1,670	\$1,652	\$1,579
Percent change	-15.8%	-0.8%	-14.8%	1.5%
# Individuals	42,426	18,244	45,658	15,012

Notes: This table presents coefficient estimates of the effects of Medicare Advantage enrollment on total medical care utilization based on the main panel and extended panel requiring continuous enrollments eight quarters prior and post age 65. For all estimates, the outcome is quarterly total allowed medical care spending, with prices normalized to FFS reimbursement rates. Results based on our preferred specification Equation (1). Changes in percentage points are rescaled estimates in terms of estimated percent change due to enrollment in MA, where control means are calculated based on the average quarterly total medical care spending at age 65 and 66 of the matched FFS cohort. “High rebate” is defined as plan payment rebates above median value; “low rebate” is defined as plan payment rebates below median value.

Appendix Table C3: Accounting Ledger (Two-year Estimates)

Current Costs		Counterfactual Costs	
Item	Cost	Item	Cost
Base Payment	+\$4,712	Average MA Costs Per 65 Year Old	+\$4,991
Rebate	+\$333	Average MA Treatment Effect	+\$701
Quality Bonus Payment		Cost-Sharing [†]	-\$854
Rebate Multiplier	+\$68		
Rebate Benchmark Adjustment	+\$90	Administrative Costs	+\$80
Base Payment Benchmark Adjustment	+\$22		
Net Upcoding Factor	+\$25		
Total (excl. rebates)	\$4,759	Total	\$4,918
Total	\$5,249		

Notes: This table presents an accounting breakdown of the current costs of offering Medicare Advantage as an option to enrolling beneficiaries (in the left panel) and the cost of counterfactually moving all MA enrollees into FFS (in the right panel). This panel analyzes these costs for enrollees at age 65 and 66, and all numbers are measured at the person-year level.

[†] Note that this is a negative cost since it is paid by beneficiaries rather than by CMS.

Appendix Table C4: Accounting Ledger: HMO vs. PPO (One-year Estimates)

Item	Current Costs		Counterfactual Costs		
	Item	Costs	Item	Costs	
	HMO	PPO		HMO	PPO
Base Payment	+\$4,552	+\$5,129	Average MA Costs Per 65 Year Old	+\$4,308	+\$5,672
Rebate	+\$451	+\$163	Average MA Treatment Effect	+\$1,336	-\$151
Quality Bonus Payment			Cost-Sharing [†]	-\$847	-\$828
Rebate Multiplier	+\$86	+\$30			
Rebate Benchmark Adjustment	+\$98	+\$78	Administrative Costs	+\$79	+\$77
Base Payment Benchmark Adjustment	+\$9	+\$54			
Net Upcoding Factor	+\$25	+\$26			
Total (excl. rebates)	\$4,586	\$5,210	Total	\$4,798	\$4,693
Total	\$5,222	\$5,481			

Notes: This table presents an accounting breakdown of the current costs of offering Medicare Advantage as an option to enrolling beneficiaries (in the left panel) and the cost of counterfactually moving all MA enrollees into FFS (in the right panel), separately for HMO and PPO plans. This panel analyzes these costs for 65-year old enrollees, and all numbers are measured at the person-year level.

[†] Note that this is a negative cost since it is paid by beneficiaries rather than by CMS.

Appendix Table C5: Accounting Ledger: HMO vs. PPO (Two-year Estimates)

Item	Current Costs		Counterfactual Costs		
	Item	Costs	Item	Costs	
	HMO	PPO		HMO	PPO
Base Payment	+\$4,471	+\$5,154	Average MA Costs Per 65 Year Old	+\$4,490	+\$5,911
Rebate	+\$432	+\$151	Average MA Treatment Effect	+\$1,678	-\$399
Quality Bonus Payment			Cost-Sharing [†]	-\$925	-\$827
Rebate Multiplier	+\$88	+\$31			
Rebate Benchmark Adjustment	+\$98	+\$75	Administrative Costs	+\$86	+\$77
Base Payment Benchmark Adjustment	+\$6	+\$50			
Net Upcoding Factor	+\$25	+\$26			
Total (excl. rebates)	\$4,503	\$5,230	Total	\$5,329	\$4,762
Total	\$5,120	\$5,487			

Notes: This table presents an accounting breakdown of the current costs of offering Medicare Advantage as an option to enrolling beneficiaries (in the left panel) and the cost of counterfactually moving all MA enrollees into FFS (in the right panel), separately for HMO and PPO plans. This panel analyzes these costs for enrollees at age 65 and 66, and all numbers are measured at the person-year level.

[†] Note that this is a negative cost since it is paid by beneficiaries rather than by CMS.

Appendix Table C6: Heterogeneity in Changes in Fiscal Cost by Plan Characteristics (One-year Estimates)

	HMO	PPO	Low Rebates Premium=0	Premium>0	High Rebates Premium=0	Premium>0
Counterfactual Cost	\$4,798	\$4,693	\$3,005	\$3,831	\$4,860	\$6,965
Full coverage	\$5,222	\$5,481	\$3,361	\$4,451	\$5,159	\$7,896
Percent change	8.8%	16.8%	11.9%	16.2%	6.2%	13.4%
Standard coverage	\$4,586	\$5,210	\$3,104	\$4,304	\$4,292	\$7,168
Percent change	-4.4%	11.0%	3.3%	12.3%	-11.7%	2.9%
Standard coverage (absent selection)	\$3,989	\$4,815	\$3,186	\$4,180	\$3,604	\$5,660
Percent change	-16.9%	2.6%	6.1%	9.1%	-25.8%	-18.7%

	Low Rebates		High Rebates	
	HMO	PPO	HMO	PPO
Counterfactual Cost	\$3,528	\$3,914	\$5,419	\$6,660
Full coverage	\$3,911	\$4,639	\$5,867	\$7,672
Percent change	10.8%	18.5%	8.3%	15.2%
Standard coverage	\$3,704	\$4,515	\$5,020	\$7,019
Percent change	5.0%	15.4%	-7.4%	5.4%
Standard coverage (absent selection)	\$3,525	\$4,538	\$4,176	\$5,266
Percent change	-0.1%	15.9%	-22.9%	-20.9%

	State MA HHI			
	Urban	Non-urban	Below median	Above median
Counterfactual Cost	\$4,502	\$4,637	\$4,813	\$4,401
Full coverage	\$5,343	\$5,218	\$5,436	\$5,252
Percent change	18.7%	12.5%	12.9%	19.4%
Standard coverage	\$4,783	\$4,805	\$5,045	\$4,682
Percent change	6.2%	3.6%	4.8%	6.4%
Standard coverage (absent selection)	\$4,220	\$4,463	\$4,575	\$4,163
Percent change	-6.3%	-3.8%	-5.0%	-5.4%

Notes: These tables report the current costs of offering Medicare Advantage as an option to enrolling beneficiaries without and with the consideration of rebates and the cost of counterfactually moving all MA enrollees into FFS for all enrollees at age 65 in the sample and separately by plan characteristics.

Appendix Table C7: Heterogeneity in Changes in Fiscal Cost by Plan Characteristics (Two-year Estimates)

	HMO	PPO	Low Rebates Premium=0	Premium>0	High Rebates Premium=0	Premium>0
Counterfactual Cost	\$5,329	\$4,762	\$3,162	\$4,141	\$5,229	\$6,599
Full coverage	\$5,120	\$5,487	\$3,315	\$4,484	\$4,859	\$7,576
Percent change	-3.9%	15.2%	4.8%	8.3%	-7.1%	14.8%
Standard coverage	\$4,503	\$5,230	\$3,080	\$4,358	\$4,029	\$6,913
Percent change	-15.5%	9.8%	-2.6%	5.2%	-22.9%	4.8%
Standard coverage (absent selection)	\$3,892	\$4,878	\$3,035	\$4,099	\$3,281	\$5,758
Percent change	-27.0%	2.4%	-4.0%	-1.0%	-37.3%	-12.7%

	Low Rebates		High Rebates	
	HMO	PPO	HMO	PPO
Counterfactual Cost	\$3,528	\$3,914	\$5,419	\$6,660
Full coverage	\$3,911	\$4,639	\$5,867	\$7,672
Percent change	10.8%	18.5%	8.3%	15.2%
Standard coverage	\$3,704	\$4,515	\$5,020	\$7,019
Percent change	5.0%	15.4%	-7.4%	5.4%
Standard coverage (absent selection)	\$3,355	\$4,514	\$3,972	\$5,401
Percent change	-4.9%	15.3%	-26.7%	-18.9%

	State MA HHI			
	Urban	Non-urban	Below median	Above median
Counterfactual Cost	\$5,039	\$4,427	\$4,751	\$4,849
Full coverage	\$5,302	\$5,125	\$5,412	\$5,188
Percent change	5.2%	15.8%	13.9%	7.0%
Standard coverage	\$4,770	\$4,753	\$5,128	\$4,620
Percent change	-5.4%	7.4%	8.0%	-4.7%
Standard coverage (absent selection)	\$4,158	\$4,477	\$4,721	\$4,040
Percent change	-17.5%	1.1%	-0.6%	-16.7%

Notes: These tables report the current costs of offering Medicare Advantage as an option to enrolling beneficiaries without and with the consideration of rebates and the cost of counterfactually moving all MA enrollees into FFS for all enrollees at age 65 and 66 in the sample and separately by plan characteristics.

Appendix Table C8: Favorable Selection of Future MA Enrollees on Total Medical Care Utilization

	One-year Estimates	Two-year Estimates		
MA_i	-148.4 (38.5)	-114.2 (19.7)	-159.1 (20.0)	-125.8 (21.4)
Pre-65 FFS baseline	\$1,247	\$1,247	\$1,225	\$1,225
Percent change	-11.9%	-9.2%	-13.0%	-10.3%
Risk scores?	✓	✓	✓	✓
Gender?	✓	✓	✓	✓
Cohort-market FEs?	✓	✓	✓	✓
Richer diagnosis FEs?		✓		✓
Race/Urban?		✓		✓
SDOH?		✓		✓
# Individuals	205,557	180,975	128,608	112,856

Notes: This table presents coefficient estimates of the favorable selection of future MA enrollees based on the main panel and extended panel requiring continuous enrollments eight quarters prior and post age 65, as measured by differences in utilization at age 64 (one-year estimates) and age 63 and 64 (two-year estimates), with prices normalized to FFS reimbursement rates. Columns 1 and 3 present estimates based on our preferred specification equation (2); columns 2 and 4 present estimates with additional controls for richer diagnosis, race, urban status, and SDOH. Changes in percentage points are rescaled estimates by control means based on the average quarterly total health care spending at age 64 of the FFS cohort for one-year estimates and at age 63 and 64 of the FFS cohort for two-year estimates.